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**UNITED STATES DISTRICT COURT**
**FOR THE SOUTHERN DISTRICT OF NEW YORK**

FEDERAL HOUSING FINANCE AGENCY, AS CONSERVATOR FOR THE FEDERAL NATIONAL MORTGAGE ASSOCIATION AND THE FEDERAL HOME LOAN MORTGAGE CORPORATION,

Plaintiff,

-against-

NOMURA HOLDING AMERICA INC., *et al.*,

Defendants.

No. 11-cv-6201 (DLC)

ECF Case

**AFFIDAVIT OF HANS ISAKSON**

STATE OF IOWA )
) ss:
COUNTY OF BLACK HAWK )

Hans Isakson, being duly sworn, deposes and says:

1. My name is Hans Isakson. I am a Professor of Economics at the University of Northern Iowa in Cedar Falls, Iowa.

2. I provide this affidavit as my direct testimony at trial. My testimony responds to the opinions of plaintiff's expert Dr. John A. Kilpatrick regarding the accuracy of appraisals performed in connection with the origination of loans underlying the seven Securitizations at issue in this Action.

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## I. Background and Qualifications

1. My qualifications to provide the opinions and conclusions in this affidavit include my (1) Ph.D. in Economics from the University of Wisconsin - Milwaukee; (2) 38 years of teaching urban economics, real estate and real estate appraisal courses at the undergraduate and graduate levels; (3) published research in real estate academic and professional journals; and (4) previous expert witness testimony.

2. I have taught real estate courses at the University of Georgia, Washington State University, University of Texas at Arlington, and University of Northern Iowa. I designed and implemented the Masters of Science degree in real estate at the University of Texas at Arlington.

3. During my academic career, dozens of my students have earned the Member Appraiser designation from the Appraisal Institute. I have authored or co-authored over 30 articles published in both academic and professional journals, including the often cited article "Using Multiple Regression Analysis in Real Estate Appraisal," *The Appraisal Journal*, Volume LXIX, Number 4 (October 2001).[1] My article "The Accuracy of Arbitrage Pricing Versus Hedonic Pricing Valuation Methodologies in Computer Assisted Mass Appraisal Systems," *Property Tax Journal* (Summer 1986) won the 1983 Lincoln Institute Manuscript Competition Award in the Colloquium on Mathematical Methods for Computer Assisted Mass Appraisal.

4. All of my expert witness work has involved rendering my expert opinion regarding real estate transactions including, but not limited to, mortgage underwriting practices, standards of practice in real estate appraisals using multiple regression analysis, and the

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[1] *See, e.g.*, *SPX Corp*. v. *Cnty. of Steele*, No. C1-00-350, 2003 WL 21729580, at *7 n.8 (Minn. Tax Ct., July 23, 2003) ("For further discussion of problems with multiple regression analysis in appraisals, see Isakson, Hans, *Using Multiple Regression Analysis in Real Estate Appraisal*, The Appraisal Journal, 424-430 (Oct. 2001).").

statistical analysis of real estate sales data. I was qualified to testify as an expert witness in one case in the past four years.

## II. Assignment

5. I was retained by counsel for Nomura Holding America Inc. and affiliated entities ("Nomura") to evaluate the work performed and opinions expressed by John A. Kilpatrick, particularly in the "Expert Report of John A. Kilpatrick, Ph.D. Concerning Accuracy of Appraisals," dated May 15, 2014 (the "Kilpatrick Report"), and the "Expert Report of John A. Kilpatrick, Ph.D.," dated October 6, 2014 (the "Kilpatrick Supplemental Report"). Specifically, I have evaluated Dr. Kilpatrick's claim that the automated valuation model ("AVM") he created for this and related litigation, the Greenfield AVM ("Greenfield AVM"), produces reliable and accurate estimates of the values of the 672 Subject Properties,[2] and I have identified and evaluated the many errors Dr. Kilpatrick made in his application of the Greenfield AVM to the Subject Properties.

## III. Summary of Opinions

6. Based on my expertise, the documents and data I have reviewed, and the analyses I have conducted, I conclude that the 8.92% difference that Dr. Kilpatrick finds between the original appraised values for the Subject Properties and the Greenfield AVM estimates of value is *not* attributable to the inaccuracy of the original appraisals, but rather to the flaws built into the Greenfield AVM and Dr. Kilpatrick's questionable scientific judgment.

7. My testimony focuses on several of the key flaws with the Greenfield AVM. In broad terms, I find that Dr. Kilpatrick systematically disregards sales prices, the best indicator of

[2] *See* Kilpatrick Report at 28-29. Note that the terms Subject Property and Subject Properties are used in this testimony to refer to the properties that secure the loans that collateralize the securities that are the subject of this case.

the market value of a house, when use of such sales prices would not support his opinions or would show that his Greenfield AVM fails to provide accurate or precise predictions of value.

8. I also find that Dr. Kilpatrick bases his analyses on a selection of "comparable sales" which are not, in fact, comparable to the Subject Properties; that the Greenfield AVM suffers from model specification errors, *i.e.*, it does not incorporate the proper explanatory variables into the its regression models (for example, he excludes the number of bedrooms but includes tax assessed value as explanatory variables); that the Greenfield AVM generates negative coefficients for several housing variables (for example, an additional bathroom often reduces the Greenfield AVM's predicted value) that in reality have a positive impact on the value of a property, in violation of both common sense and the hedonic pricing model he purports to use; and that the Greenfield AVM contains several additional systemic statistical flaws, including the use of a level of statistical significance inconsistent with accepted scientific standards.[3]

## IV. Summary of Dr. Kilpatrick's Opinions

9. Dr. Kilpatrick opines, using his Greenfield AVM, as to whether "the original appraisals used to value the collateral and generate the LTV [loan-to-value] ratios associated with a sample of the subject loans underlying the 7 supporting loan groups ('SLGs') that support the 7 Securitizations at issue in this Action . . . were accurate."[4] Dr. Kilpatrick formulates his opinion based upon his analysis of (i) a sample of 796 loans for the Subject Properties provided to him by Dr. Charles Cowan,[5] (ii) "appraisal-related information" from "loan tapes" and "loan

[3] Statistical significance results when it can be shown with a pre-selected level of confidence (usually 95% or more) that an observed relationship has *not* occurred merely by chance.

[4] Kilpatrick Report at 1-2.

[5] *Id.* at 18.

files,"[6] and (iii) a sample of 49 million sales of residential properties and "nationwide tax and deed data" provided to him by CoreLogic.[7]

10. Dr. Kilpatrick claims that his Greenfield AVM is a retrospective AVM that can accurately value specific properties on given dates in the past. Dr. Kilpatrick also represents that the Greenfield AVM is a "hedonic pricing model," which is a "form of multiple regression analysis."[8] Multiple regression analysis is a statistical technique that identifies the relationship between a set of variables. Multiple regression analysis helps one understand how the value of a "dependent" variable changes when any one of multiple "independent" or "explanatory" variables changes, while the remaining explanatory variables are held constant. Explanatory variables are variables that are used to explain or predict changes in the values of another variable, called the dependent variable. For example, in a model that purports to determine the value of houses, the number of bedrooms is an important explanatory variable which can help explain the value of a house, the dependent variable.

11. A hedonic equation specifies the value of a house as a function of its characteristics, and is based upon a well-established theory called implicit markets theory. For example, in a highly simplified hedonic equation, we can specify the value of a house (V) as a simple linear function of just one characteristic, say its living area measured in square feet (SqFt). Then, we can express this relationship as:

$$\mathrm{V} = a^{*}\mathrm{SqFt},$$

[6] *Id.* at 18-19.

[7] *Id.* at 19-21.

[8] *Id.* at 3-4, 26-29, 33, 36-38, 41-42.

in which *a* represents the value of a square foot of living area.[9] The characteristics chosen in a hedonic equation and their relationships to the value of a house must be based upon sound theory; otherwise, the estimates produced by the equation will be unfounded. For example, in implicit markets theory, the assessed value of a house is not considered a legitimate characteristic because it is not a determinant of the value of a house.

12. A hedonic model specifies the coefficients (for example, the value of *a* in the above equation) to estimate the change in value resulting from a unit change in a component characteristic, holding all else constant.[10] Thus, the coefficients determine the ability of each explanatory variable to predict the value of the dependent variable accurately. The coefficients must conform to the underlying theory (implicit markets theory) upon which the equation is based. For example, because the square footage of living area should positively impact the value of a house, the coefficient *a* in the above equation should not be negative.

13. The Greenfield AVM employs two multiple regression models to produce its estimates of property values: (i) an ordinary least squares regression model ("OLS") and (ii) an OLS model with an additional "trend surface component" ("OLSXY").[11] When used appropriately, the OLS is a very common type of model and the simplest method of linear regression, which is designed to closely "fit" a function (estimate the coefficients of the equation). Dr. Kilpatrick states that, with respect to the OLSXY model, "[t]he use of the trend

[9] Technically, the relationship between V and SqFt should be non-linear. However, I use a linear relationship here to simplify this discussion. By using a linear relationship, nothing about this discussion of implicit markets theory would be affected except the functional form of the equation. In addition, there is usually an intercept term in the equation, which I have suppressed for simplicity.

[10] Kilpatrick Report at 4 n.5

[11] *Id.* at 30.

surface component allows the model to incorporate spatial effects (value impacts due to location) into the valuation."[12]

14. There are three "required" explanatory variables in the Greenfield AVM's OLS model: (i) (natural log of) tax assessed value, (ii) days, and (iii) days squared.[13] The dependent variable is the natural logarithm of the sales price. Dr. Kilpatrick reports that tax assessed value is used as a "proxy variable for other unobserved or unavailable structural and locational characteristics."[14] "Days" are, according to Dr. Kilpatrick, "a measure of the number of days between an origin date and the date of sale."[15] In addition to the three required variables used in the OLS model, the OLSXY model incorporates five additional "required" explanatory variables: latitude, longitude, latitude squared, longitude squared, and latitude multiplied by longitude.[16] According to Dr. Kilpatrick, these five trend surface explanatory variables in the OLSXY model are meant to "approximate distance between the subject property" and the properties that serve as purportedly comparable sales in the Greenfield AVM, as explained below.[17] The OLS and OLSXY models also incorporate "other available variables . . . [when] present in sufficient quantity for the regression," such as living area (square footage), lot size, age of the structure, and number of bathrooms.[18]

15. Dr. Kilpatrick estimates the coefficients for the explanatory variables in the OLS and OLSXY models using up to 2,000 of the geographically (meaning in the same County as the

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[12] *Id.*

[13] *Id.* at 33.

[14] *Id.* at 38.

[15] *Id.* at 39 n.105.

[16] *Id.* at 34.

[17] *Id.* at 40.

[18] *Id.* at 33-34.

Subject Property) and temporally (meaning within one year of the origination of the loan for the Subject Property) closest CoreLogic sales data that are of the same property type (detached residential or condominium) as the Subject Property. As explained by Dr. Kilpatrick, "[w]hen a subject property is valued using the Greenfield AVM, the characteristics of nearby sales are used to specify the model and determine the coefficients of the underlying hedonic models."[19] In other words, the Greenfield AVM uses the relationship between the selling prices and explanatory variables in the CoreLogic data and then applies this relationship to the Subject Properties to obtain estimates of their market values.

16. The Greenfield AVM also uses a "cross-validation" technique, which is not a required step in applying the OLS technique, to eliminate CoreLogic sales when the Greenfield AVM poorly predicts their selling prices. Specifically, the Greenfield AVM applies the OLS and OLSXY models to produce a predicted value for each of the CoreLogic sales and then selectively disregards many sales, purportedly because these discarded sales are "suspect transactions."[20] Dr. Kilpatrick identifies these suspect transactions (predicted sales) using an arbitrarily selected cross-validation value discussed below.

17. After the Greenfield AVM removes the purportedly "suspect transactions," it re-estimates the regression coefficients for the OLS and the OLSXY models, separately and independently, using the artificially pruned CoreLogic sales data to predict the value of each Subject Property. If both the OLS model and OLSXY model return predicted house values, then these values are averaged for a final estimate of value called the "reconciled value"[21] of each Subject Property. The Greenfield AVM does not compare its predicted value for a Subject

[19] *Id.* at 29.

[20] *Id.* at 33.

[21] Kilpatrick Report at 34.

Property, which is heavily influenced by the tax assessed value explanatory variable, with the actual selling price of any Subject Property.

18. Dr. Kilpatrick also attempts to estimate the accuracy and precision of the Greenfield AVM using a process he calls a "calibration" exercise. In this exercise, he runs the Greenfield AVM on an artificially pruned and highly selective set of the CoreLogic sales data. Dr. Kilpatrick states that he culls down the 49 million CoreLogic sales by eliminating: (i) sales before 2004 and after 2007, (ii) transactions with "missing transactional" data, and (iii) transactions outside the "middle 30th percentile" of sales price to assessed value ratio (purportedly to eliminate more suspect data).[22] He does not report how many sales were eliminated by each of these three "filters," but does report that after applying these filters he is left with 708,098, or only 1.4%, of the original 49 million CoreLogic sales.[23] He further reports that he culls down the 708,098 CoreLogic sales by eliminating (i) properties that were "built (or rebuilt) after the end of the sample period (end of 2007)" and (ii) properties that have "valuation errors of greater than 100%."[24] These additional filters leave only 675,613 of the original 49 million CoreLogic sales.[25] Dr. Kilpatrick does not report how the "valuation errors of greater than 100%" were calculated.[26] Dr. Kilpatrick reports that, for purposes of his calibration exercise, he randomly splits the filtered CoreLogic data into two sets: 90% are used to estimate the coefficients of the Greenfield AVM, and these coefficients are then used to predict the values

[22] *Id.* at 46-47.

[23] *Id.* at 47.

[24] *Id.* at 50.

[25] *Id.*

[26] *Id.*

of the remaining 10%.[27] He generates various statistics to support his claim that the Greenfield AVM is "reliable and accurate, has sufficient coverage across the nation, performs exceptionally well, and is entirely appropriate to utilize in performing retroactive appraisals."[28]

19. Dr. Kilpatrick contends that the values generated by the Greenfield AVM represent the "true" market values of the Subject Properties,[29] and finds, based on his results, that "the average original appraisal in the sample Nomura loans was overvalued by 10.67% . . . with a median of 6.41%."[30] He then removed six more of the loans for the Subject Properties and arrives at a final "mean bias" of 8.92%.[31] In other words, Dr. Kilpatrick claims that the original appraisals of the remaining 672 Subject Properties, on average, overstated the market value of the properties by 8.92%. He concludes that "no reasonable, competent appraisal professional adhering to appraisal standards applicable at the time could, in [Dr. Kilpatrick's] opinion, validate the Nomura Appraisals as reliable, unbiased, or accurate."[32]

20. Using the lowest of (i) the Greenfield AVM estimate of value, (ii) the original appraised value, and (iii) the sales price of the Subject Properties (for those Subject Properties with a selling price), Dr. Kilpatrick recalculated the loan-to-value ("LTV") ratios for the loans secured by the Subject Properties at the time of origination.[33] He also calculated mixed loan-to-value ratios ("MLTVs") for each of the seven SLGs and claims that "the Nomura sample

[27] *Id.* at 46-47.

[28] *Id.* at 57.

[29] *Id.* at 63.

[30] *Id.* at 60.

[31] *Id.* at 61.

[32] *Id.* at 66-67.

[33] *Id.* at 67-69.

loans had substantially higher MLTV ratios than represented [in the relevant prospectuses]."[34] He states that the differences between the average LTV ratio using the appraised value for each loan and the average recalculated LTV for these Subject Properties is "significant across all SLGs."[35]

## V. Dr. Kilpatrick Selectively Ignores Sales Prices

21. It is well established that the sales price in an arm's-length transaction represents the best indicator of the "true market value" of a house.[36] An arm's-length transaction occurs when the buyer and seller of a property are on equal footing (*i.e.*, neither has an undue influence on the other) and the sale occurs in a competitive market environment.[37] Under these conditions, the agreed-upon sales price is treated by appraisers and most real estate professionals to be the true market value of the house. Dr. Kilpatrick seems to agree: the definition of market value he purports to apply in his analysis states that "[m]arket value means the most probable price which a property should bring in a competitive and open market under all conditions requisite to a fair sale, the buyer and seller each acting prudently and knowledgeably, and assuming the price is not affected by undue stimulus."[38]

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[34] "MLTV, which is used to evaluate the aggregate lien position risk for a bundle of securitized loans, was determined as follows. For first-position loans, I took the LTV ratio, and for second-position loans, I took the CLTV ratio. Finally, I determined the simple average of these MLTV ratios for each SLG." *Id.* at 69.

[35] *Id.* at 70.

[36] For discussions of arm's-length transactions being the best indicator of market value of a house, *see* Stephens, W., *et al.* (1995), Conventional Mortgage Home Price Index, *Journal of Housing Research*, Volume 6, Number 3, pp. 389-418, esp. 390; CoreLogic GeoAVM Model Methodology, Creating and Testing the GeoAVM Cascade Models, Unpublished White Paper, 2009, p. 2; recent comments by FNMA's Chief Economist David Berson quoted in Leventis, A., Removing Appraisal Bias from a Repeat-Transactions House Price Index: A Basic Approach, Office of Federal Housing Enterprise Oversight Working Paper 06-01, Feb. 2006, p. 9; Notice, *Federal Register*, Volume 75, Friday, Dec. 10, 2010/Notices, p. 77469.

[37] A competitive market exists when there are many buyers and sellers such that each buyer and each seller has a negligible impact on the market price. *See* Mankiw, N.G. (2009), *Principles of Microeconomics, 6th Edition*, Mason, Ohio: South-Western Cengage Learning, p. 66.

[38] Kilpatrick Report at 76.

22. Dr. Kilpatrick disregards the sales prices of the Subject Properties, however, when those sales prices would undermine the purported accuracy of the Greenfield AVM. In particular, Dr. Kilpatrick: (i) selectively ignores the sales prices of the Subject Properties (for purchase money mortgages) when defining "true" market value; (ii) eliminates over 70% of CoreLogic data (based on price-to-assessed-value ratios) when calculating the Greenfield AVM's accuracy and precision; and (iii) applies a statistically flawed cross-validation filter that, among other things, eliminates relevant sales data.

**A. Dr. Kilpatrick Ignores the Actual Sales Prices of the Subject Properties**

23. Despite having the actual selling price available for 45.5% (306 out of 672)[39] of the Subject Properties, Dr. Kilpatrick claims that his Greenfield AVM reconciled value is instead the "true" market value for each Subject Property.[40] Dr. Kilpatrick ignores the available selling prices for the Subject Properties, yet fails to provide any evidence that even one sale of a Subject Property was not an arm's-length transaction. Instead, Dr. Kilpatrick assumes, without evidence, that the Subject Property sales are "incorrect sales transaction[s]."[41] Despite this unjustifiable rejection of the selling prices of the Subject Properties, Dr. Kilpatrick implicitly regards the selling prices in the CoreLogic data, which he uses to estimate the values of the Subject Properties, as correct and legitimate market transactions equivalent to what he calls "true" market values. However, the "comparable" CoreLogic sales that Dr. Kilpatrick uses are comparable to the Subject Properties only in that they (i) are in the same county, (ii) have sold

[39] These 306 Subject Properties received Greenfield AVM valuations and secured purchase-money loans that are at issue in this matter. (*See* Kilpatrick Report, Appendix 6-1.)

[40] Kilpatrick Report at 63.

[41] Deposition of John Kilpatrick, dated Feb. 13, 2014 ("Kilpatrick Feb. 13 Tr."), at 358:9-11.

within a year of the Subject Property's original appraisal, and (iii) are of the same housing type as the Subject Properties.

24. Had Dr. Kilpatrick compared the Greenfield AVM estimates of value to the actual selling prices of the 306 Subject Properties with a selling price, he would have discovered that the Greenfield AVM was more than 13% in error (relative to the actual selling prices of the Subject Properties) 45.8% of the time (140 out of 306). Therefore, only 54.2% (166 out of 306) of the Greenfield AVM reconciled values were within 13% of the actual selling prices of the Subject Properties. This percentage (54.2%) fails to meet the Freddie Mac suggested concentration that at least 70% of the estimates of any AVM (which would include the Greenfield AVM) must be within 13% of the actual sales prices of the Subject Properties.[42] In other words, when the Greenfield AVM is subjected to an objective comparison to the actual selling prices of the Subject Properties, it fails to meet the same industry standard that Dr. Kilpatrick cites and uses to support his opinion that the Greenfield AVM is reliable, accurate and "entirely appropriate to utilize in performing retroactive appraisals on the sample Nomura Properties."[43]

25. Dr. Kilpatrick claims to have compared the Greenfield AVM results to sales transactions in response to these criticisms.[44] However, for the 306 properties with sales prices to compare, Dr. Kilpatrick still insists on applying arbitrary filters. Dr. Kilpatrick eliminated the top 5% and top 10% of properties with the greatest difference between the Greenfield AVM results and the sales price.[45] He claims that there were "data discrepancies" in these properties,

[42] *See* Kilpatrick Report at 50-51.

[43] *Id.* at 57.

[44] Expert Report of John A. Kilpatrick, dated October 6, 2014 ("Kilpatrick Supplemental Report"), at 6.

[45] *Id.*

but again provides no evidence of such data errors. Yet, Dr. Kilpatrick's claim, that the Greenfield AVM estimates are "within approximately 1 percent on average"[46] of the selling prices of the Subject Properties, only holds after he eliminates the Subject Properties that produced the largest errors.

26. The Greenfield AVM calculates what it states is a "true" market value that is higher than the actual selling price of a Subject Property 42.3% of the time (129 out of 306). Yet, as I explain below, Dr. Kilpatrick disregards these inconvenient 129 Greenfield AVM "true" market values when he calculates LTV ratios.

27. Specifically, when running the Greenfield AVM, Dr. Kilpatrick uses the sales price of each Subject Property when those prices support his conclusion and disregards them when they do not. In re-calculating the LTV ratios for the Securitizations, Dr. Kilpatrick uses as values (the denominator of the LTV ratio) the *lesser* of (1) the Greenfield AVM estimate, (2) the original appraised value, or (3) the sales price, for purchase money loans.[47] For refinance mortgages, Dr. Kilpatrick calculates LTV ratios using values equal to the *lesser* of (1) the Greenfield AVM or (2) the appraised value. In fact, when calculating LTV ratios, Dr. Kilpatrick uses the Greenfield AVM estimate as market value only 64.3 percent of the time—thus at least 35.7% of the time contradicting his contention that the Greenfield AVM represents the "true" market value. As a result, Dr. Kilpatrick does not allow the inconveniently high Greenfield AVM estimates of "true" market value to influence his opinions.

[46] *Id.*

[47] *Id.* at 67-69. Dr. Kilpatrick attempts to justify his "lesser of" calculation on the grounds that it is a common industry practice to calculate contemporaneous LTV ratios using the lesser of the contract purchase price or a contemporaneous appraised value. The Greenfield AVM reconciled values are not contemporaneous appraisals, however. Dr. Kilpatrick claims instead that they represent the "true" values of the Subject Properties. Kilpatrick Report at 63. If Dr. Kilpatrick believes that his Greenfield AVM provides the "true" value for a property, he should exclusively use that value to calculate LTV ratios.

28. The effects of Dr. Kilpatrick's selective and biased calculations of LTV ratios can be found in Table 6-7 of the Kilpatrick Report.[48] This table contains the original LTV of the loans in this matter as shown in the Prospectus Supplements. The average of these original LTV ratios is 80.29% (average of the second column of Table 6-7). Using Dr. Kilpatrick's method of calculating the LTV ratios, as described above, yields the selective and biased average of 90.43% (average of the third column in Table 6-7). It is biased because, by using the "lesser of" the Greenfield AVM value, the sales price, or the appraised value, he can only ever find that the LTV ratio was inflated. If Dr. Kilpatrick believes that the Greenfield AVM estimate of value is the "true" market value, then he should have exclusively used it in the denominator of the LTV ratios. To estimate the effect of eliminating this particular flaw, I requested Dr. Jerry Hausman to recalculate the LTV ratios using the Greenfield AVM estimates exclusively, instead of using Dr. Kilpatrick's "lesser-of" method. The average LTV ratio, when exclusively using the Greenfield AVM estimates, is 86.72%. These recalculated ratios are, on average, 3.71 percentage points below those reported by Dr. Kilpatrick in Table 6-7. In other words, Dr. Kilpatrick's failure to exclusively use the Greenfield AVM's so-called true market values causes his reported LTV ratios to be overstated by 36.6%.[49]

### B. Dr. Kilpatrick Artificially Prunes Away Over 70% of the CoreLogic Data to Falsely Shrink the Greenfield AVM Forecast Standard Deviation in His Calibration Exercise

29. To calculate the accuracy and precision of the Greenfield AVM, Dr. Kilpatrick seeks to calculate a forecast standard deviation ("FSD") for his model. To do so, Dr. Kilpatrick

[48] *Id.* at 70.

[49] This figure (36.6%) is equal to (90.43– 86.72) / (90.43 – 80.29) and represents the fraction of Dr. Kilpatrick's purported overstatement of the LTV ratios (90.43 – 80.29 = 10.14) explained by his failure to exclusively use the Greenfield AVM estimates (90.43– 86.72 = 3.71).

randomly splits the CoreLogic housing sales data for each county into a training set (90%) and a holdout set (10%) in an attempt to statistically validate the Greenfield AVM. Next, Dr. Kilpatrick eliminates from his 10% holdout set (i) valuations for CoreLogic housing sales outside of the middle 30th percentile of sale-price-to-assessed-value ratios in each county and (ii) sales for which the Greenfield AVM produces errors greater than 100 percent. Dr. Kilpatrick states—without further explanation—that he has taken this step to "eliminate suspect data."[50]

30. Although this "90/10" technique is not unusual, the elimination of regression observations with high or low sale-price-to-assessed-value ratios (outside the middle 30th percentile) and transactions that the Greenfield AVM does not fit well (errors greater than 100%) is scientifically unsupportable. Dr. Kilpatrick's biased selection of a well-behaved subset of the data (*i.e.*, symmetric, close to the mean, and having absolutely no outliers) on which to evaluate the model gives the Greenfield AVM an appearance of precision and reliability when, in fact, the model validation fails to account for the model's predictive performance for more than 70% of the holdout set.

31. To illustrate, the narrow shaded strip in Figure 1 shows the middle 30th percentile of a standard normal distribution.[51] Figure 1 illustrates that choosing the middle 30th percentile for any dataset is artificial. Dr. Kilpatrick discards all of the observations to the left and right of the middle 30th percentile (70%) *before* he calculates the accuracy and precision of the Greenfield AVM using the remaining data. By eliminating any potential outliers (non-shaded areas in Figure 1), Dr. Kilpatrick artificially reduces the overall variation by using only the shaded strip. Furthermore, the middle 30th percentile (shaded area) in a normally distributed

[50] Kilpatrick Report at 47, 50.

[51] Note, however, that the distribution of the CoreLogic sale-price-to-assessed-value ratio is not normal; it is not symmetric and it is highly affected by outliers.

dataset is, by itself, a well-behaved dataset. If a dataset is not normally distributed—for example, the CoreLogic dataset—then trimming the outliers has an even more acute impact, and amounts to removing large prediction errors, rather than simply measuring the model's actual performance. In other words, Dr. Kilpatrick is pruning the data to fit the (Greenfield AVM) model, rather than crafting a model that fits the data.

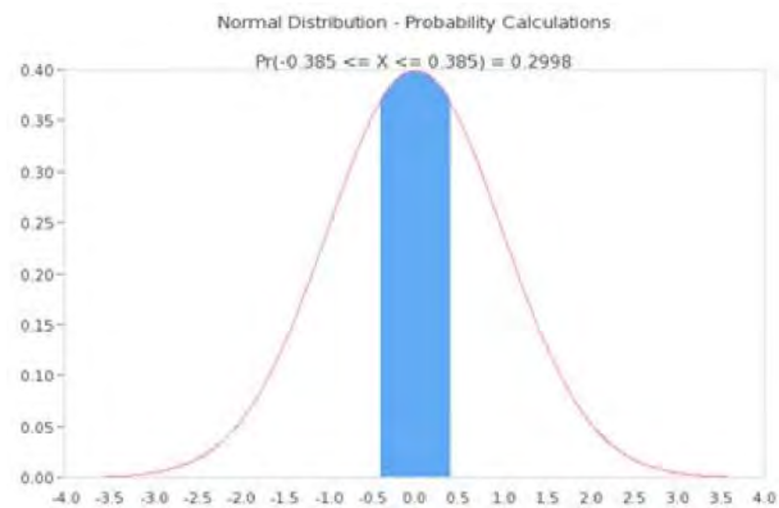


Figure 1: The Middle 30th Percentile of a Standard Normal Distribution
Source: http://mathcracker.com/normal_probability.php

32. As a result of Dr. Kilpatrick's selective and biased data pruning process, the "industry standard statistics" calculated by Dr. Kilpatrick to attempt to measure the precision of his model only potentially hold for the middle 30th percentile of any other set of sales data. The claim that the Greenfield AVM is adequately accurate and precise for all sets of housing data constitutes an unjustified claim.[52] In effect, Dr. Kilpatrick manipulates the Greenfield AVM's

[52] Using the model in these circumstances introduces extrapolation errors. Extrapolation is the process of estimating, beyond the original observation interval, the value of a variable on the basis of its relationship with another variable. Prediction errors tend to increase when extrapolating beyond the original observation interval. *See* Loh W.Y., Chen C.W., and Zheng, Z. (2007), Extrapolation Errors in Linear Model Trees, *ACM Transactions on Knowledge Discovery*, 1:2, pp. 1-17; *see also* Bardach, E. (2004), Presidential Address—The Extrapolation Problem: How Can We Learn From the Experience of Others?, *Journal of Policy Analysis and Management*, 23:2, 205-20 for a partial discussion of the extrapolation problem.

prediction results to make them appear better than they would be if the Greenfield AVM were applied to unfiltered housing data.

33. The programs that Dr. Kilpatrick produced in the backup materials to the Kilpatrick Report allow for determination of the true, unfiltered, and unbiased industry metrics, including, *inter alia*, the FSD and the percentage of model predictions within 13% of the actual selling price for the Greenfield AVM.[53] Therefore, I directed Analysis Group to recalibrate the Greenfield AVM's industry metrics for various central percentiles (for example 70th, 80th . . . 100th) for the same holdout set that Dr. Kilpatrick uses. Analysis Group retained all of the other filters (elimination of errors greater than 100%, application of the Cross Validation (CV=.25) filter when running the Greenfield AVM itself, etc.) built into Dr. Kilpatrick's calculations in his calibration analysis. In particular, as presented in Figure 2, using the entire (100th percentile) holdout set causes the Greenfield AVM's FSD to rise from 15.1% to 23.8%. Figure 2 also illustrates that once sales other than those in the central 40th percentile are considered, the Greenfield AVM's FSD rises dramatically.

34. Using the entire (100th percentile) holdout set also causes the fraction of reconciled valuations within 13% of the actual sales price to fall from the 74.4% reported in the Kilpatrick Report to 59.8%—well below Freddie Mac's performance standards for AVMs (70% of valuations are expected to have an FSD of 13% or less) cited by Dr. Kilpatrick in his report.[54] This is similar to the performance of the Subject Properties, for which only 54.2% had Greenfield AVM values within 13% of the actual selling prices (as discussed above at ¶ 24). In both cases, the Greenfield AVM fails to meet the industry standards cited by Dr. Kilpatrick.

[53] PrepareCVTestData.R, produced as backup material to the Kilpatrick Report.

[54] Kilpatrick Report at 50-51.

35. In addition, the recalibrated Greenfield AVM's industry metrics (coefficient of dispersion, coefficient of variation, and price-related differential)[55] using the entire holdout set also fail to meet the industry standards cited by Dr. Kilpatrick. Hence, Dr. Kilpatrick's filtering of the CoreLogic data to conclude that the Greenfield AVM "is entirely appropriate to utilize in performing retroactive appraisals on the sample Nomura [Subject] properties"[56] artificially and inaccurately overstates the accuracy and precision of the Greenfield AVM. When the calibration exercise is performed exactly as Dr. Kilpatrick reports with one exception, the elimination of the middle 30th percentile filter, I find that the Greenfield AVM is *not* reliable, *not* accurate, did *not* perform exceptionally well, and should *not* be used to value the Subject Properties in this matter.

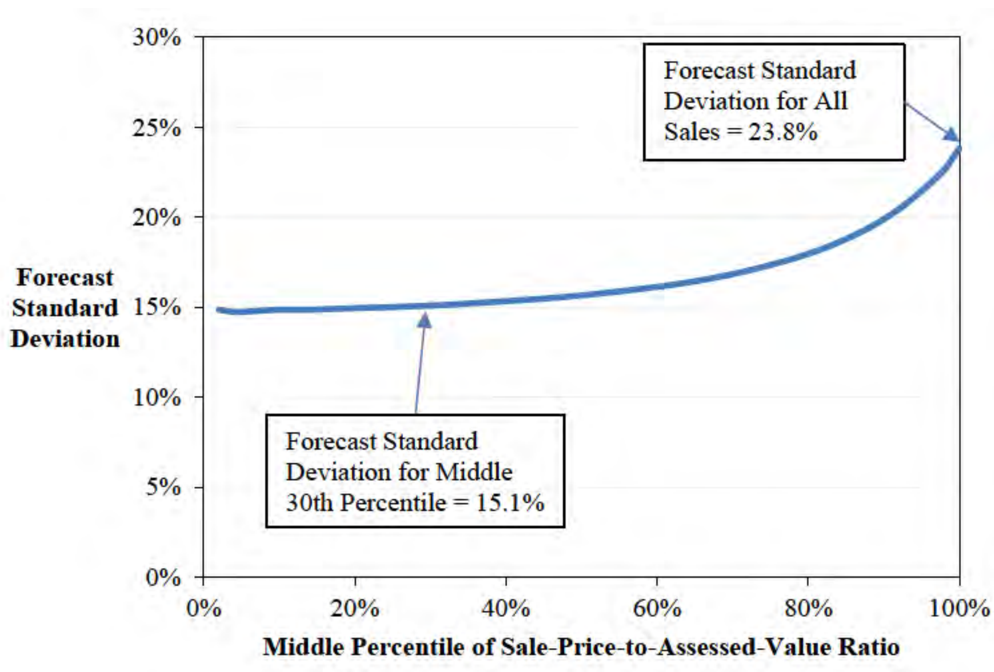


Figure 2: Sensitivity of the Greenfield AVM's FSD to Changes in the Central Percentile of Sales in the Holdout Set

[55] *Id.* at 57, esp. Table 5-2.

[56] *Id.*

### C. Dr. Kilpatrick Uses Improper Cross-Validation Techniques

36. In addition to the middle 30th percentile filter illustrated in Figure 2, the Greenfield AVM contains an additional filter, called the cross-validation (CV=.25) filter, that is specifically designed to eliminate CoreLogic sales whose actual prices are not well predicted by the Greenfield AVM.[57] After the initial regression observations are selected and the Greenfield AVM produces initial estimates of value, the Greenfield AVM performs the "cross-validation" procedure as follows: The Greenfield AVM calculates the errors from the initial Ordinary Least Squares (OLS) regressions and proceeds to delete the regression observations with the "largest" errors. Dr. Kilpatrick defines the "largest" errors using a cross-validation cut-off value at 0.25, which purportedly "approximates a two-standard-deviation range around a mean error of 0."[58] In other words, the Greenfield AVM eliminates any CoreLogic transactions for which the Greenfield AVM fails to predict their actual selling prices accurately. Then, the Greenfield AVM re-estimates the values of the Subject Properties using the thinned data set.

37. This data thinning process eliminates observations in a manner that is inconsistent with both the principles of the OLS technique, purportedly used by Dr. Kilpatrick,[59] and how an appraiser would arrive at an estimate of value (as discussed below). The fundamental purpose of

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[57] *See* Kilpatrick Report at 32-33, 59-60.

[58] Kilpatrick Report at 60 n.158. The mean error is always zero for any OLS regression. *See* Neter, J., Kutner, M., Nachtsheim, C., and Wasserman, W. (1996), Applied Linear Statistical Models, 4th Edition, McGraw-Hill, p. 97.

[59] A fundamental purpose of any OLS regression (including those in the Greenfield AVM) is to reduce the unexplained variability of the dependent variable (to increase the precision for its predicted value given a set of independent variables) by adding additional independent or explanatory variables, not deleting regression observations. More explanatory power can be acquired by adding columns (explanatory variables) to the model, not removing rows (deleting regression observations), because, formally, the variance of Y will be reduced when adding explanatory variables, X, (*i.e.*, $Var(Y) \geq Var(Y|X)$). As the result of deleting observations rather than adding explanatory variables, Dr. Kilpatrick's CV process is not consistent with the principles of the OLS technique. *See* Neter, *et al.*, *supra* note 58.

this Greenfield AVM data thinning step is to achieve an artificially low FSD.[60] Again, Dr. Kilpatrick prunes data by deleting observations only to exaggerate the precision of the Greenfield AVM. In particular, in applying the cross-validation filter, Dr. Kilpatrick: (i) impermissibly engages in what statisticians refer to as "data snooping"; (ii) eliminates sales data for no other reason than it does not fit his model; (iii) creates a built-in contradiction which allows CoreLogic sales to be inconsistently classified as both legitimate and illegitimate depending upon which regression is being run; and (iv) in some instances drastically reduces the available regression observations for a Subject Property.

### 1. Dr. Kilpatrick Engages in Data Snooping

38. Data snooping occurs when a given set of data is used more than once for the purpose of inference or statistical model specification.[61] So, by definition, Dr. Kilpatrick engages in data snooping when he thins data using the CV=.25 filter and then re-uses only the data that passes muster to predict house value. Fayyad, *et al.* (1996) cautions that data snooping, such as that in the Greenfield AVM's CV process, "can be a dangerous activity leading to discovery of meaningless patterns."[62]

### 2. Dr. Kilpatrick Ignores Inconvenient Sales Data

39. What is particularly troublesome is that the data thinning in the Greenfield AVM has nothing to do with testing whether an individual sale (a regression observation used in the Greenfield AVM) possesses any apparent unique characteristic that would disqualify it as a valid regression observation (*e.g.*, not being an arm's-length transaction). Instead, Dr. Kilpatrick

[60] Kilpatrick Feb. 13, 2014 Dep. at 353:2-4.

[61] White, H. (2000), A Reality Check for Data Snooping, *Econometrica*, 68:5, pp. 1097-1126.

[62] Fayyad, U., Piatetsky-Shapiro, G., and Smyth, P. (1996), The KDD process for extracting useful knowledge from volumes of data, *Communications of the ACM*, 39:3, pp. 28-29.

identifies observations that do not fit his model well using his CV=.25 criterion and then he immediately removes them. His argument is circular: if a regression observation does not fit the Greenfield AVM model well (it was filtered out using the CV=.25 criterion) then it must be removed because it is a "suspect transaction."[63] In other words, Dr. Kilpatrick removes transactions, where there is no evidence that they were not arm's-length, for no other reason than that the Greenfield AVM does not do a good job of predicting their values.

40. It is important to note that just because a data value is an outlier does not mean it must be automatically removed from the analysis. In particular,

> the first question that should be asked is whether there exists some *substantive information* about these points that suggests that they should be removed. Do they involve special properties or circumstances not relevant for the situation under investigation? Do they involve possible measurement errors? If no such distinguishing features can be found, then there are no clear grounds for eliminating outliers.[64]

Statistics textbooks advocate a more cautious approach to removing outliers than that used by Dr. Kilpatrick. For example, Weiss says,

> Generally, an outlier should not be removed without careful consideration. Simply removing an outlier because it is an outlier is unacceptable statistical practice.[65]

Neter, *et al.* explain further that,

> . . . outliers may convey significant information, as when an outlier occurs because of an interaction with another predictor variable omitted from the model. A safe rule frequently suggested is to discard an outlier only if there is direct evidence that it represents an error in recording, a miscalculation, a malfunction of equipment, or a similar type of circumstance.[66]

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[63] Kilpatrick Report at 33.

[64] *Id.*

[65] Weiss, N.A. (2008), *Introductory Statistics, 8th edition*, New York, Addison Wesley, p. 387.

[66] Neter, *et al.*, *supra* note 58, at 103.

In addition, federal agencies, especially the National Institutes of Health and the National Science Foundation, consider *omitting data* to be research misconduct when the results are not "accurately represented."[67] Furthermore, one should perform the regression

> both *with* and *without* these outliers, and examine their specific influence on the results. If this influence is minor, then it may not matter whether or not they are omitted. On the other hand, if their influence is substantial, then it is probably best to present the results of *both* analyses, and simply alert the reader to the fact that these points may be questionable.[68]

41. Dr. Kilpatrick provides no substantive explanation as to why these outliers or any sales should be removed from the analysis, apart from his conclusory assertion that they are "non-representative transactions."[69] Nor does he provide any direct economic or statistical metric to allow an assessment of the impact of their removal. As I explain below, there is an artificial, six-fold decrease in Greenfield AVM prediction errors caused solely by the cross-validation process.

42. The cross-validation process eliminates certain sales for no other reason than Dr. Kilpatrick's unsubstantiated claim that the regression observations used to calculate the Greenfield AVM reconciled values are ensured to be "legitimate market transactions,"[70] therefore implying that the eliminated sales are not "legitimate market transactions." These sales, if included, would increase the FSD and mean squared error ("MSE") for the Greenfield AVM. Dr. Kilpatrick picks regression observations (using a CV=.25 criterion) that will sufficiently prune the data to fit the Greenfield AVM. Choosing a different value of the cross-

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[67] 42 C.F.R. § 93.103.

[68] *See* www.seas.upenn.edu/~ese302/extra_mtls/REGRESSION_OUTLIERS.pdf.

[69] Kilpatrick Report at 32.

[70] *Id.* at 60 n.158.

validation statistic (other than 0.25) will produce a different set of regression observations which, in turn, will produce a different predicted value (and MSE and FSD).

43. Pruning regression observations has serious consequences. By eliminating certain observations arbitrarily, Dr. Kilpatrick under-reports the true FSDs and MSEs (regression variability) of the Greenfield AVM estimates of value. The sales eliminated are those with the greatest errors, so that the model's fit for the remaining sales will appear to be more precise than it actually is. My analysis shows that, as a result of Dr. Kilpatrick's erroneous cross-validation process, the variability in the estimates of market value reported by Dr. Kilpatrick (post-CV filter) is understated by a six-fold factor when compared to the variability in the Greenfield AVM before applying the CV filter. I reached this result by replicating the Greenfield AVM for the Subject Properties. I compare the Greenfield AVM MSEs for both the OLS and OLSXY regressions[71] pre-filtering versus post-filtering, *i.e.*, before and after Dr. Kilpatrick's application of the CV=.25 criterion. In applying the Greenfield AVM to the Subject Properties, Dr. Kilpatrick's use of the CV=.25 filter reduces the variability (MSE pre-filtering divided by MSE post-filtering) by an average factor of 13.4 (median reduction is 6.4) for the 672 OLS regressions. For the 671 OLSXY regressions, the trimming process reduces the variability at about the same level as for the OLS Greenfield AVM model: the average reduction factor is 12.6 (median is 6.3). Without the CV=.25 filter, there would be (conservatively) a six-fold increase in the variability of the Greenfield AVM.

[71] The Greenfield AVM includes two regressions that Dr. Kilpatrick calls the OLS and OLSXY regressions. *See Id.* at 30.

### 3. The Cross-Validation Process Contains a Built-in Contradiction

44. Another problem with Dr. Kilpatrick's cross-validation process is that it is performed separately and independently for the OLS and OLSXY models, and thus sales deemed to be legitimate market transactions in the OLS model may not be considered legitimate in the OLSXY model (and *vice versa*). Because the regression observations before the CV filter is applied are selected in an identical fashion for both regressions (OLS and OLSXY), the regression observations for the OLS model *must be* identical to those of the OLSXY model. If there is a difference in the number of regression observations between the two models after the CV filter has been applied, then one model *must have* rejected some of the sales as being "suspect" transactions, while these same "suspect" transactions were deemed valid sales in the other model.

45. In my analysis of the Subject Properties, I found that only 39 of the 672 Subject Properties—or just 5.8%—had the same number of regression observations for both the OLS and the OLSXY models. For the vast majority—94.2%—of the Subject Properties, the number of regression observations in the OLS model are not the same as those in the OLSXY model (for the same Subject Property). In other words, *94.2 percent of the time* the Greenfield AVM identifies some sales as "suspect" transactions in one regression but legitimate in the other. For example, GLN NAA_2005_AR6_1002008184 had 382 regression observations that were declared to be "suspect transactions" in the OLSXY model, but were perfectly fine for the OLS model.[72]

[72] This Subject Property had 1,326 OLS and 944 OLSXY regression observations.

#### 4. The Cross-Validation Process Can Drastically Reduce the Sales Data

46. Finally, the CV data thinning process dramatically trims the number of regression observations for some of the Subject Properties. For example, Global Loan Number ("GLN") NHELI_2006_HE3_2002205584 had 1,998 original, pre-data thinning regression observations. The application of the cross-validation filter resulted in a 91.1% data reduction, leaving the Greenfield AVM OLSXY regression with a sample size of only 178. Dr. Kilpatrick's claim that 91.1% of the 1,998 original regression observations for GLN NHELI_2006_HE3_2002205584 are "suspect" transactions is made without any foundation. Instead, Dr. Kilpatrick apparently eliminated these observations because they did not give him the statistical results he sought.

47. In sum, for the reasons described above, Dr. Kilpatrick's Greenfield AVM data thinning step is statistically unsound, scientifically improper, and highly misleading.[73] Its use reflects highly unsound judgment and improper scientific techniques by Dr. Kilpatrick.

### VI. Dr. Kilpatrick's Greenfield AVM Selects Regression Observations that Are Incompatible with Established Appraisal Practices for Selecting Comparable Sales

48. Real estate appraisers employ drastically different techniques than the Greenfield AVM to select the data used in estimating the market value of houses. The processes used by appraisers and the Greenfield AVM are compared in greater detail below to illustrate why the Greenfield AVM selects incompatible regression observations.

49. When real estate appraisers apply the Sales Comparison Approach[74] to estimate the value of a house, they collect data on recent sales of comparable houses. The houses that are

[73] *See* Seltzer, W., U.S. Federal Statistics and Statistical Ethics: The Role of the American Statistical Association's Ethical Guidelines for Statistical Practice, unpublished manuscript, Department of Sociology and Anthropology, Fordham University, http://iranethics.ir/files/site1/pages/the_role_of_the_american_statistical_associations.pdf.

[74] Appraisal Institute, *The Appraisal of Real Estate, 12th Edition*, 2001, Chapters 17-19.

the "most comparable"[75] are selected for more in-depth analysis. The appraiser "estimates the degree of similarity or difference between the subject property and the comparable sales by considering various elements of comparison,"[76] including physical characteristics and location.

50. Academic studies have shown that using all of the information available concerning the characteristics of a subject property when selecting comparable sales is superior to using only one characteristic, such as proximity to the subject property. In the selection of comparable sales using a multidimensional measure of similarity, a weighted average of three comparable sales can produce an estimate of value more accurate than that produced by an OLS regression.[77] Further studies demonstrate empirically that the selection of comparable sales in a manner similar to how appraisers select them is superior to how Dr. Kilpatrick selects them.[78]

### A. Geographical Housing Submarkets: Zip Codes

51. When selecting representative sales, appraisers strive to find comparable properties as similar as possible to the subject property.[79] By contrast, after rudimentary filtering, the Greenfield AVM strives to find regression observations that optimize its FSD.[80] The regression observations in the Greenfield AVM are not equivalent to the comparable sales that an appraiser uses. Appraisers select comparable sales by matching as many of the

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[75] *Id.* at 63.

[76] *Id.*, pp. 63, 417.

[77] Isakson, H.R. (1986), The Nearest Neighbors Appraisal Technique: An Alternative to the Adjustment Grid Method, *Journal of the American Real Estate and Urban Economics Association*, 14:2, pp. 274-86.

[78] *See, e.g.*, Gau, G.W., Lai, T.Y., and Wang, K. (1992), Optimal Comparable Selection and Weighting in Real Property Valuation: An Extension, *Journal of the American Real Estate and Urban Economics Association*, 20:1, pp. 107-123; Vandell, K. (1991), Optimal Comparable Selection and Weighting in Real Property Valuation, *Journal of the American Real Estate and Urban Economics Association*, 19:2, pp. 213-39.

[79] Real estate appraisers generally call the property they are appraising the "subject property" (lower case) in contrast to the Subject Properties (upper case) that were defined earlier.

[80] Kilpatrick Feb. 13, 2014 Dep. at 353:2-4.

characteristics of the comparable properties to the characteristics of the subject property, while the Greenfield AVM selects regression observations without regard to the physical characteristics (*i.e.*, living area, number of bathrooms, lot size, etc.) of the subject property.[81] In addition, the Greenfield AVM omits some regression observations based on an arbitrary statistical criterion, namely the cross-validation process.

52. Initially, the Greenfield AVM selects regression observations by proximity to the Subject Property and date of sale. Sales occurring within one year of the date of the loan secured by the Subject Property and in the same county as, and in close proximity to, the Subject Property are considered for selection. The Greenfield AVM requires at least 100 sales and never uses more than 2,000 of the nearest sales.[82]

53. Uniformly defining the county of each Subject Property as the market area for that property, as the Greenfield AVM does, is problematic, especially in larger counties. Most counties consist of many municipal jurisdictions (cities and towns) and housing submarkets. Selecting comparable sales from one submarket to estimate the value of a house in another submarket will produce inaccurate and unreliable estimates of value.[83] The Greenfield AVM neither identifies nor recognizes the importance of real estate submarkets. Instead, the Greenfield AVM uses only geographic proximity within a county to artificially construct a real estate submarket for each Subject Property.

54. An examination of the zip codes of the Greenfield AVM regression observations reveals an alarming pattern: the majority of the Greenfield AVM OLSXY regression

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[81] Kilpatrick Report at 32-34; *The Appraisal of Real Estate*, *supra* note 73, at 371-75.

[82] Kilpatrick Report at 59.

[83] Goodman, A.C. and Thibodeau, T. G. (1998), Housing Market Segmentation, *Journal of Housing Economics*, Volume 7, pp. 121-43 and Appraisal Institute (2007), *Appraising Residential Properties, 4th Edition,* Chapter 10, Neighborhood and Market Area Analysis, pp. 197-219.

observations are located in a zip code other than that of the Subject Property. A zip code is typically smaller than an entire county and, therefore, it is a better definition of the market area of the Subject Property than the entire county in which the Subject Property is located. At my request, Dr. Hausman compiled zip code data for all 671 Greenfield AVM post-CV filtered OLSXY regressions. When I compared the zip code of the Subject Property to the zip codes of its corresponding regression observations, I found that the Greenfield AVM OLSXY regressions had 66.7% of their regression observations located in a zip code other than that of the Subject Property.[84] Worse yet, only seven of the 671 (1.0%) Greenfield AVM OLSXY regressions have *nearly all* (99% or more) of the regression observations located in the same zip code as that of the Subject Property. At the other extreme, the OLSXY regression for one Subject Property uses regression observations from *83* different zip codes. A competent appraiser prefers not to select comparable sales from a city or zip code other than that of the Subject Property.[85]

55. Figures 3, 4, and 5 illustrate the effects of using geographical proximity to define the market areas for the Subject Properties. These three Figures represent the best (Figure 3), average (Figure 4), and worst (Figure 5) sets of Greenfield AVM regression observations. The regression observations in Figure 3 represent one of the seven in which nearly all of the regression observations are located within the same zip code ([redacted]) as the Subject Property (NHELI_2006_FM1_2002169144). Yet, even in this best case situation of

[84] The 671 Greenfield AVM OLSXY regressions use a total of 969,165 regression observations and 961,561 have a known zip code. Only 320,587 of the OLSXY regression observations with a known zip code (33.3%) are located within their corresponding Subject Property's zip code.

[85] It is possible that if a subject property is right on the border between two zip codes, a competent appraiser *might*, as a last resort, select one or more comparable sales from the adjacent zip code if, and only if, no comparable sales could be found within the same zip code as that of the subject property. If this unusual situation were to arise, the competent appraiser would be obligated to make an adjustment (*see The Appraisal of Real Estate*, pp. 435-36) for the fact that a comparable sale is located in a zip code other than that of the subject property. The Greenfield AVM makes no such adjustments.

the Greenfield AVM, some regression observations are drawn from two nearby cities ([redacted] and [redacted]), while the Subject Property is located in a Census Designated Place called [redacted].

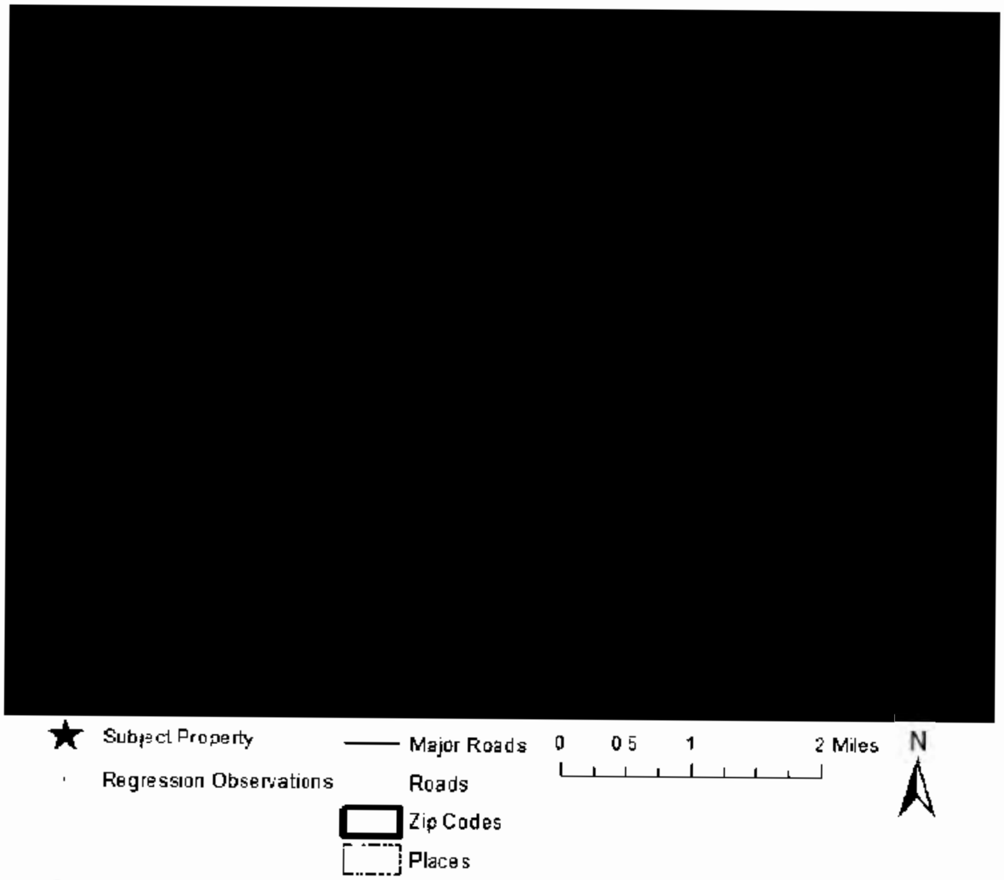


Figure 3: All Regression Observations in the Same Zip Code as Subject Property

56. Figure 4 illustrates a representative Greenfield AVM set of regression observations. On average, the Greenfield AVM selects regression observations from nine zip codes. When regression observations are taken from multiple zip codes, such as those in Figure 4, it becomes more likely that the regression observations will come from housing submarkets that are very different from that of the Subject Property. Notice that many of the regression observations in Figure 4 are located in cities different than that of the Subject Property (NHELI_2006_HE3_2002013470, [redacted]). Not only are the regression observations drawn from different zip codes, they are drawn from different towns ([redacted],

[redacted] and [redacted]). A closer look at Figure 4 reveals that there are ample sales located within the same zip code and city as that of the Subject Property from which a competent appraiser could find a sufficient number of comparable sales for application of the sales comparison approach.[86]

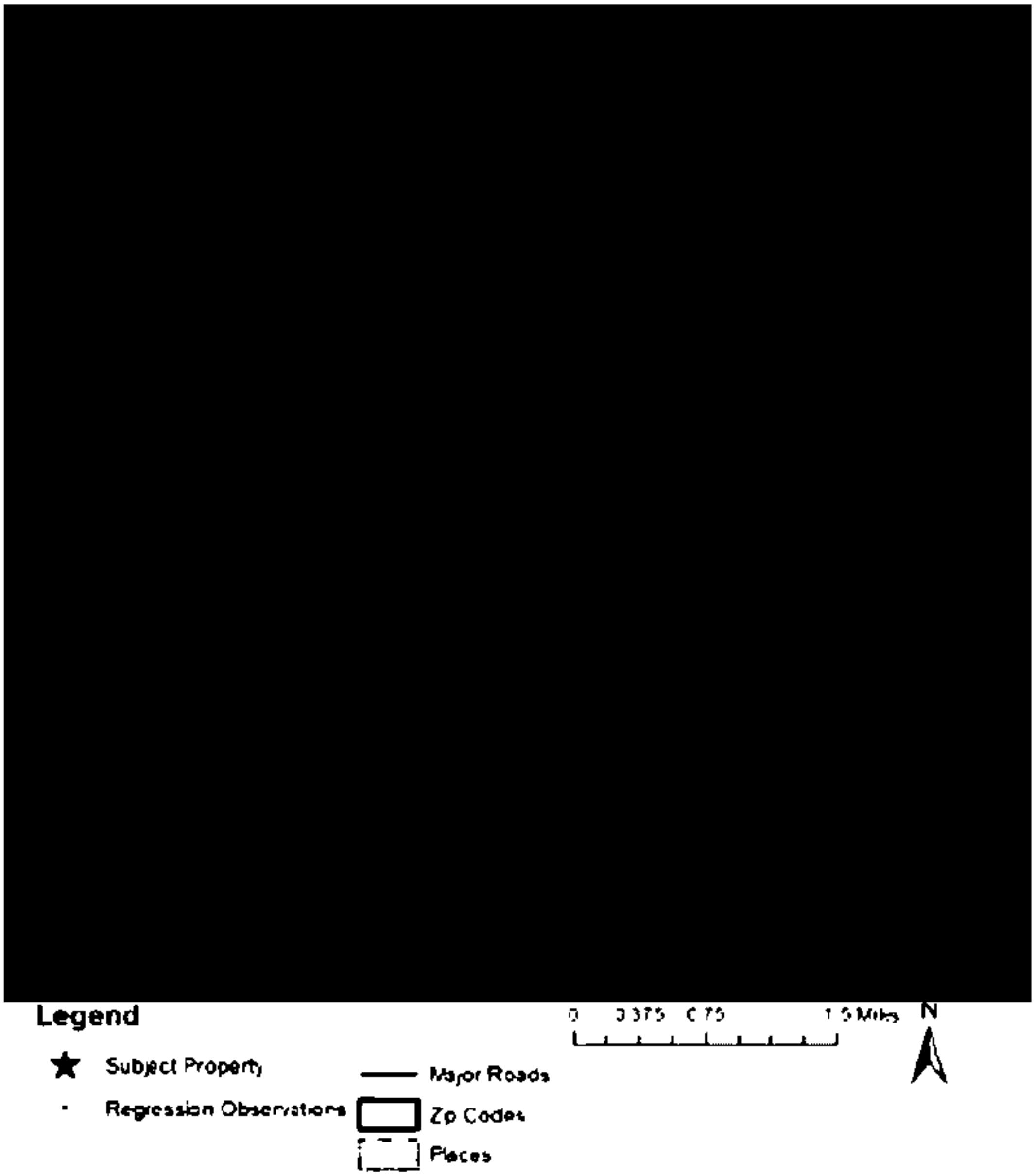


Figure 4: Regression Observations Located in an Average (9) Number of Zip Codes

[86] *The Appraisal of Real Estate*, *supra* note 73, at chs. 17-19.

[redacted]

Subject Property
Regression Observations
Major Roads
Zip Codes
0 4 8 16 Miles
N

Figure 5: Regression Observations in 83 Zip Codes

57. The regression observations seen in Figure 5 are located in 83 different zip codes, with all but two being in a zip code other than that of the Subject Property (NHELI_2007_2_ 2002148962, [redacted]). In Figure 5, many of the regression observations are located in different housing submarkets than, and more than 10 miles away from, the Subject Property. Even though the Subject Property is located in the southeast quadrant of the urban area, regression observations are taken from all of the quadrants of the urban area. A competent appraiser—who has not discarded a significant amount of properties out of hand—would have no problem finding comparable sales located within a few blocks of the Subject Property in Figure 5.

58. As the above maps illustrate, even under the best of conditions (where all regression observations are in the same zip code as the Subject Property), the actual regression

observations used by the Greenfield AVM to estimate the value of the Subject Properties are being drawn from housing submarkets that are very different from the housing submarket of the Subject Property. Nothing in the Greenfield AVM controls for these differences. A competent appraiser would not select comparable sales that would result in supposed comparables as geographically diverse as the regression observations used by the Greenfield AVM.

### B. Changing Market Conditions Over Time

59. Within any particular housing submarket, market conditions change over time as the forces of supply and demand change. In general, the market value of a house reflects the market conditions at the time of the sale. When market conditions are changing rapidly, it is difficult to adjust estimates of market value for time. Never was this problem more acute than during the 2002 to 2007 period, when the average annual rate of appreciation in U.S. housing prices jumped from approximately 6% in 2001 to over 12% by 2005.[87] All appraisals for the 672 mortgages secured by the Subject Properties were conducted during this period of rapidly escalating housing prices.

60. The Greenfield AVM contains two explanatory variables (days and days-squared) to account for changing market conditions during the twelve months prior to the origination date of the loans in this matter. This is not adequate to account for the changing market conditions described above. By including days-squared, the Greenfield AVM allows for one change point in the rate of growth in housing prices during the twelve months prior to the origination of the loans in this matter. The problem with this specification is that the growth rate may change more than once during a year, especially when prices are increasing rapidly.

[87] Levitin, A. and Wachter, S. (2012), "Explaining the Housing Bubble," MPRA Paper No. 41920, p. 29.

## VII. Flaws Created by Using Tax Assessed Value as an Explanatory Variable in the Greenfield AVM

61. The Greenfield AVM contains several errors in the specification of the OLS models: (i) it incorrectly includes assessed value for the Subject Properties as an explanatory variable; (ii) it omits important explanatory variables; and (iii) it cannot simultaneously be a hedonic and a tax assessment adjustment model.

### A. Assessed Value Is Not a Proper Explanatory Variable and Was Used Incorrectly by Dr. Kilpatrick

62. Tax assessed value is commonly used to measure property taxes at the tax jurisdiction level. In a sense, a property's assessed value represents the value of the property for tax purposes. Outside of tax purposes, assessed value has limited applicability due to limitations imposed by taxing jurisdictions' assessment policies. In particular, such limitations make the use of assessed value in a hedonic price model (such as the Greenfield AVM) problematic.

63. For example, 17 states place limits on the annual increase in assessed value.[88] These limits drive a wedge between the assessed value and the market value of a house, and reduce any correlation between assessed value and market value (even within a jurisdiction), which in turn can make assessed value an unreliable predictor of market value. Similarly, reappraisal cycles vary among states and counties. Differences in the frequency of reassessing house values can lead to inconsistency in the relationship between a property's assessed value and its market value. The most common reappraisal cycle is one year. However, two states reassess properties every two years, seven states reassess every three years, and 13 states employ

[88] Dornfest, A.S., Van Sant, S., Anderson, R., and Brown, R. (2010), State and Provincial Property Tax Policies and Administrative Practices (PTAPP): Compilation and Report, *Journal of Property Tax Assessment & Administration*, 7:4, p. 59.

reappraisal cycles of four years or longer.[89] So, even if tax assessors were 100% accurate in estimating the value of a house, that estimate would be accurate only at the time of reassessment because house values change over time. In eight states (CT, IN, IA, MO, NY, RI, VT, and WI) and the District of Columbia, houses are assessed in jurisdictions smaller than a county, borough, parish, etc.[90] In these states, the policies and practices of local tax assessors can vary within a particular county, borough, parish, etc. Because the Greenfield AVM selects regression observations from the same county as the Subject Property (rather than from the same taxing jurisdiction), the relationship between assessed value and market value can vary across properties within the same county.

#### 1. Assessed Value Is Not a Determinant of Market Value and Cannot Be Used to Reliably Predict Market Value

64. Hedonic pricing theory requires that explanatory variables in a hedonic price model include only characteristics and features of a house that determine or influence the value of a house. For example, the living area of a house has an influence on the value of a house; a change in the living area of a house *causes* the value of the house to change. Dr. Kilpatrick uses the assessed value of each regression observation as an explanatory variable in the Greenfield AVM in violation of hedonic pricing theory, while maintaining in his report that the OLS and OLSXY models in the Greenfield AVM are hedonic pricing models.[91] A change in the assessed value of a house does not cause its market value to change. Rather, changes in the market value of a house may (but will not always, depending on timing, the relevant legal regime, and the

[89] *Id.*, 19.

[90] *Id.*, 42.

[91] Kilpatrick Report at 3-4, 26-29, 33, 36-38, 40-42.

homeowner's actions) cause its assessed value to change.[92] This systemic error seriously undermines the theory on which the Greenfield AVM is built.

65. Others who apply hedonic pricing theory almost never include assessed value as an explanatory variable. For example, in a study cited and relied upon by Dr. Kilpatrick, none of the 125 published hedonic studies use assessed value as an explanatory variable.[93] Dr. Kilpatrick argues, unsuccessfully, that it is better "to use the assessed value in the model as a more objective indicator of and proxy for quality and condition" of the house.[94] Although an argument can be made for proxy variables in hedonic pricing theory, there is no valid argument for using assessed value as a proxy variable for missing variables, such as quantity and quality of the characteristics of a house. Assessed value is not included in the list of housing features frequently used by researchers.[95] In addition, in a study co-authored by Dr. Kilpatrick that used two hedonic pricing models, the assessed value of a house is *not* used as an explanatory variable in either model.[96] Not only do other researchers exclude assessed value as an explanatory variable in hedonic models of the housing market, but even Dr. Kilpatrick excluded it in one of his published studies.[97]

66. Using assessed value as an explanatory variable in a hedonic model introduces other problems. First, the assessed value of a house is estimated by tax assessors and therefore can and does contain errors. Thus, assessed value has a prediction error, so technically it is the

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[92] The Appraisal of Real Estate, *supra* note 73, at 141.

[93] Sirmans, G.S., MacPherson, D.A., and Zietz, E.N. (2005), The Composition of Hedonic Pricing Models, Journal of Real Estate Literature, 13:1, at 1-44.

[94] Kilpatrick Report at 36 n.96.

[95] Sirmans, *et al.*, *supra* note 92, at 1-44.

[96] Kilpatrick, J.A., Throup, R.L., Carruthers, I., and Krause, A. (2007), The Impact of Transit Corridors on Residential Property Values, *Journal of Real Estate Research*, 29:3, pp. 303-320.

[97] *See infra* notes 113 and 114.

observed amount of a random quantity. True characteristics of a house, such as living area and number of bathrooms, can be measured accurately and tend to be invariant over time. Assessed values are not static; they vary over time as tax assessors reassess the value of houses. The Greenfield AVM does not account for these measurement errors caused by the injection of the tax assessor's judgment and practices in his/her calculation of assessed values.

67. Second, as described above, there is no consistent correlation between assessed value and market value, even within the same geographic locales. For example, in California there is a limit on how much the assessed value of a house can increase from year to year, and houses are assessed at market value only when they change owners.[98] Accordingly, in California, houses with very similar market values may have very different assessed values, making assessed values a very poor proxy for the quality and quantity of the characteristics of a house (and a very poor predictor of market values). In many jurisdictions, especially those that reassess house values infrequently, tax assessors find it very difficult to keep assessed values up-to-date when market values are rapidly changing.[99] Again, houses with similar market values may have different assessed values because of the vagaries of the state and local laws governing how and when house values are assessed.

68. Third, house owners can and do appeal the assessed value of their houses in an effort to reduce their property taxes. The fact that every taxing jurisdiction has a mechanism for appealing an assessed value affirms the heterogeneity of assessed value and, by extension, the fact that it is inappropriate as a proxy for missing variables such as "quality and condition" in the

[98] *See* Cal. Const., Art. 13A (as amended).

[99] *See* Rafool, M. (2002), A Guide to Property Taxes: An Overview, National Conference of State Legislatures, Washington, DC, p. 6.

Greenfield AVM.[100] Some but not all owners appeal their properties' assessed valuations, which can induce additional heterogeneity in the relationship of assessed value and market value.[101] Consequently, these factors render assessed values very poor proxy variables for the "quality and condition" of a house.

### 2. Even if Assessed Value Could Properly Be Used as an Explanatory Variable, Dr. Kilpatrick Used It Incorrectly

69. Dr. Kilpatrick claims that he "designed the Greenfield AVM to take into account the kinds of information that competent, reasonable appraisers would have available to them in their normal course of work."[102] This claim implies that the assessed value information used in the Greenfield AVM would have been available to appraisers at the time of the Subject Properties' original appraisals. Indeed, for the Greenfield AVM to produce a proper "retrospective" estimate of value, that principle must hold true, and in particular the Tax Year of each Subject Property and its corresponding comparables must be contemporaneous with (or earlier than) the date of the original appraisals in this matter. However, the Kilpatrick Report is completely silent about the Tax Year of the assessed values of the Subject Properties and "comparable" regression observations used in the Greenfield AVM.

70. To test for the contemporaneous dates of the original appraisals and assessed values, I directed Analysis Group to produce a summary of the Tax Years of the Subject Properties. This summary is presented in Defense Exhibit 2810 ("DX-2810"). As shown in DX-2810, the Greenfield AVM used assessed values of the Subject Properties that were established

[100] Kilpatrick Report at 36 n.96.

[101] Certainly, owners whose property assessed values are less than what they believe the market value of their house to be would have no incentive to go through the appeal process because the result would be a higher, not a lower, tax bill. Additionally, many owners may be reluctant to engage in the appeal process for a variety of reasons, *e.g.*, insufficient time to invest in the appeal process, lack of confidence in a successful appeal.

[102] Kilpatrick Report at 25.

well after the origination of the loans that are secured by the Subject Properties. Indeed, for *all* but four of the Subject Properties for which Tax Year information was available, the Greenfield AVM used an assessed value taken from a Tax Year from 2010 to 2014. When compared to the date of the original appraisals, the Tax Year of the Subject Property's assessed value is *at least four years* and, on average, *6.3 years after* the date of origination of the loans in this matter.

71. Dr. Kilpatrick's use of *post-hoc* assessed values is inconsistent with his expressed opinions. According to Dr. Kilpatrick's explanation of his work, the Greenfield AVM relies on inputs, including assessed value, that were available at the time of the original appraisal for each Subject Property.[103] It would be impossible, however, for appraisers who performed the original appraisals to know the future assessed value of a Subject Property. Dr. Kilpatrick fails to provide any rationale or explanation as to why it is appropriate to use *future* assessed values to estimate the retrospective value of the Subject Properties.

72. In addition, using future values to estimate present day values is logically and professionally unsound. Dr. Kilpatrick's use of future assessed values may be compared to an appraiser using future living area to estimate the value of a house in the present, simply because the owner intends to add an extra 1,000 square feet to the house in the future.

73. Treating assessed value as a traditional hedonic explanatory variable, such as living area, number of bathrooms, etc., is also unjustified because (among other things) market conditions in 2010 – 2014 (the Tax Years of the Subject Properties) are not the same as the market conditions in 2004 – 2006 (when the loans at issue in this matter were originated). In particular, housing prices fell dramatically after 2006 and have not fully recovered in all markets, which could lead to tax assessed values in 2010 – 2014 that are lower than those in 2004 – 2006.

[103] *Id.*

In my opinion, the use of present day assessed values in calculating so-called "retrospective" Greenfield AVM estimates of value completely invalidates all of Dr. Kilpatrick's opinions that are based upon the results of the Greenfield AVM.

74. Finally, the use of present day assessed values to estimate retrospective market values assumes that the relationship between assessed values and market values (selling prices) does not change over time. The coefficient of assessed value in the Greenfield AVM represents the relationship Dr. Kilpatrick claims exists between the selling prices and assessed values of the regression observations. This relationship can change over time, especially when market conditions are changing. For example, during the 2005 through 2007 time period, incomes were rising and interest rates were very low, increasing demand for houses. Rising demand for houses can lead to rising house prices as buyers pay higher prices for higher quality features of a house, such as a three car garage rather than a two car garage; granite countertops rather than laminate; wood or ceramic tile floors rather than carpet; etc. When demand for houses falls, as was occurring when assessed values of the regression observations and Subject Properties were established, housing prices tend to fall and buyers are less willing to pay premium prices for premium features of a house. Yet for all the reasons discussed above, tax assessed values do not necessarily change in tandem with market values. Thus, using assessed values established during a declining market to estimate the values of the Subject Properties during a rising market renders the Greenfield AVM estimates unreliable.

75. In sum, including assessed value as an explanatory variable in the Greenfield AVM is problematic because (i) assessed value is not a determinant of market value, (ii) assessed value contains tax assessor biases and other measurement errors, and (iii) assessed value does not generally have a consistent relationship to market value, even within the same locale. Even if

assessed value could be used properly as an explanatory variable in a hedonic pricing model, Dr. Kilpatrick uses it incorrectly by failing to use assessed values contemporaneous with the origination of the loans in this matter. By using *post-hoc* assessed values, the Greenfield AVM fails to produce retrospective estimates of value, even according to Dr. Kilpatrick's definition of retrospective estimates of value. These problems associated with using assessed value as an explanatory variable could have been avoided by excluding assessed value from the Greenfield AVM and directly incorporating the explanatory variables for which Dr. Kilpatrick believes assessed value serves as a proxy.

**B. Dr. Kilpatrick Ignores Key Determinants of Market Value**

76. Considerable insight into the intricacies of a particular housing market is needed to build a dependable and reliable hedonic model. The problem of omitted variables is frequently found in applications of the OLS technique to hedonic pricing models[104] of a housing market, primarily because no particular set of housing characteristics works well in all housing markets, *i.e.*, housing markets in the United States are not homogeneous. For example, in some markets, the outside view (perhaps of mountains, a body of water, a city vista, etc.) is an important explanatory variable, while in other markets all houses have similar views. The problem of omitted variables exists because all housing markets are heavily influenced by (i) their geographic location and (ii) the tastes and preferences of the population in that location. Thus, a set of explanatory variables that works well in one market can often fail to work well in another market. Building a hedonic pricing model of the housing market in any particular area

[104] The Greenfield AVM purports to be such a model: "Functionally, the Greenfield AVM takes the industry-leading form of a hedonic ordinary least squares ("OLS") model." Kilpatrick Report at 3-4.

requires the analyst to know which housing characteristics are important to buyers and sellers of houses in that particular market.

77. The Greenfield AVM suffers from missing variables and excludes all but a select few explanatory variables. It blindly applies the variables it does use across all housing markets, without regard to how particular markets behave. Competent appraisers spend considerable time studying the housing characteristics that buyers and sellers value and use these characteristics when matching comparable sales to a subject property.

78. Previous studies show that there are several key house characteristics common in hedonic pricing models, including lot size, living area, number of bathrooms, number of bedrooms, and garage size.[105] The Greenfield AVM includes, at most, two of these important house characteristics: living area and number of bathrooms. Dr. Kilpatrick justifies the omission of number of bedrooms on the grounds that number of bedrooms and living area are highly correlated. But he reports this correlation to be 0.55.[106] In other words, only about 30 percent (0.55 squared) of the variation in number of bedrooms is explained by the variation in living area. Some correlation always exists among the various characteristics of houses, but in my opinion, a correlation of 0.55 is simply too low to justify the exclusion of number of bedrooms as an explanatory variable. Indeed, any data analyst should be aware that a regression measures joint correlations, not marginal correlations. Thus, the statistical significance of the number of bedrooms in the full regression model is much more important than its marginal correlation (0.55) with the living area. In other words, the correlation (0.55) that Dr. Kilpatrick reports as

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[105] Exhibit 1 in Sirmans, *et al.*, *supra* note 92, lists lot size, square feet, brick exterior, age, number of stories, number of bathrooms, number of rooms, bedrooms, full baths, fireplace, air-conditioning, basement, garage spaces, deck, pool, distance (typically distance from the city center), time on market, and time trend among the twenty characteristics most frequently found in hedonic regression equations.

[106] Kilpatrick Report at 36 n.96.

being high does not imply that the number of bedrooms would not contribute significantly to the explanatory power of the Greenfield AVM.

79. As a result of this omission, the Greenfield AVM suffers from omitted variables bias. In spite of Dr. Kilpatrick's claim that a correlation of 0.55 is high, including number of bedrooms as a variable in the Greenfield AVM would increase the explanatory power of the Greenfield AVM substantially. Omitting the number of bedrooms variable, or any other relevant explanatory variable, would change the Greenfield AVM's estimates of the values for the Subject Properties. This systemic methodological flaw renders the Greenfield AVM estimates of value inaccurate, imprecise, and unreliable.

### C. The Greenfield AVM Cannot Simultaneously Be a Hedonic and a Tax Assessment Adjustment Model

80. When confronted in his deposition with the problem of using assessed value as an explanatory variable, Dr. Kilpatrick claimed that the Greenfield AVM is a tax assessment adjustment model,[107] in direct contradiction of his claim that the Greenfield AVM is a hedonic model.[108] It cannot simultaneously be a hedonic and a tax assessment adjustment model, despite what Dr. Kilpatrick claims.[109] Indeed, if the Greenfield AVM were some type of assessed value adjustment model, then Dr. Kilpatrick uses it incorrectly, because tax assessment adjustment models are intended to reveal biases made by tax assessors, not to estimate individual house values. In short, using assessed value as an explanatory variable results in a mis-specified hedonic model.

[107] Deposition of John Kilpatrick, November 13, 2014 ("Nov. 13, 2014 Dep.") at 123:17-21.

[108] Kilpatrick Report at 3-4, 26-29, 33, 36-38, 40-42.

[109] Kilpatrick Nov. 13, 2014 Dep. at 124:2-8.

81. Using the (natural logarithm of) assessed value as an explanatory variable and the (natural logarithm of) selling price as the dependent variable creates the additional potential problem of heteroscedasticity[110] in the Greenfield AVM. The Greenfield AVM regressions in the model can be expressed as a simple equation:

$$\log(market\ value) = \alpha + \beta * \log(assessed\ value) + \boldsymbol{\gamma} * \boldsymbol{C},$$

where $\boldsymbol{C}$ = a vector of other explanatory variables (*e.g.*, time, time squared). The Greek letters represent the coefficients to be estimated by the regression. From an econometric perspective, the regression equation above is problematic because it has *value* on both sides of the equation. This heteroscedasticity problem can be corrected simply by subtracting [β * log(*assessed value*)] from both sides of the equation to get:

$$\log(market\ value) - \beta * \log(assessed\ value) = a + \boldsymbol{\gamma} * \boldsymbol{C}.$$

It is important to move assessed value to the left-hand side of the equation because it and market value are random variables. That is, market value and assessed value are measured with considerable error, which will introduce bias in the estimate of the relationship between market value and assessed value. However, moving assessed value to the left-hand side, where it belongs, transforms the Greenfield AVM from a hedonic model to a type of tax assessment ratio model, similar to the models found in assessment ratio studies.[111] Moreover, the equation above (with the market and assessed values on the left-hand side) cannot be estimated using the OLS technique; some other statistical technique must be used, such as the maximum likelihood

[110] In simple terms, heteroscedasticity means that the variation of the dependent variable is highly correlated with one of the independent variables. Its presence can invalidate statistical tests for significance.

[111] *See* Berry, B.J.L. and Bednarz, R.S. (1975), A Hedonic Model of Prices and Assessments for Single-Family Homes: Does the Assessor Follow the Market or the Market Follow the Assessor?, *Land Economics*, 51:1, pp. 21-40 and Kowalski, J.G. and Colwell, P.F. (1986), Market versus Assessed Values of Industrial Land, *AREUEA Journal*, Volume 22, pp. 361-365 for examples of assessment ratio models.

technique. These systemic errors make the Greenfield AVM estimates of value inaccurate, imprecise, and unreliable.

### D. An Assessment of Dr. Kilpatrick's Justifications for Using Future Tax Assessed Values in the Greenfield AVM

#### 1. Justifications Cited by Dr. Kilpatrick

82. Dr. Kilpatrick justifies the use of assessed value as an explanatory variable for the following reasons: (i) assessed value is "a more objective indicator of and proxy for quality and condition"[112]; (ii) assessed value is "a proxy variable for other unobserved or unavailable structural and locational characteristics"[113] of sales price to changes in the assessed value"; (iii) assessed value "measures the elasticity or responsiveness of sales price to changes in the assessed value"[114]; (iv) using assessed value makes the Greenfield AVM a tax assessment adjustment model[115]; and (v) others use assessed value as an independent variable[116] in a regression with selling price as the dependent variable.

#### 2. Analysis of Dr. Kilpatrick's Justifications for Using Tax Assessed Value

83. Tax assessed value does not determine the market value of a house; it is not a causative factor. Although Dr. Kilpatrick claims in his deposition that the Greenfield AVM is not a "causality model,"[117] he previously implied that a change in assessed value causes the market value of a house to change, when he says that the coefficient of assessed value "measures

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[112] Kilpatrick Report at 36 n.96

[113] Kilpatrick Report at 38.

[114] Kilpatrick Report at 43 n.122.

[115] Kilpatrick Nov. 13 Dep. Tr. at 117:2-6.

[116] Kilpatrick Report at 38 n.100.

[117] Kilpatrick Nov. 13 Dep. Tr. at 127:23.

the elasticity or responsiveness of sales price to changes in the assessed value."[118] Therefore, using assessed value as an explanatory variable is inconsistent with a Rosen-type hedonic model.

84. Assessed value is not a composite characteristic of a house; the composite characteristics of a house include things such as its living area, number of bathrooms and bedrooms, year built, size of the garage, etc. But, augmenting a Rosen-type hedonic model (see Section VII) with non-house characteristics represents a clear specification error.[119]

85. Dr. Kilpatrick claims that tax assessed value is a proxy variable for "unobserved or unavailable structural and locational characteristics" in order to avoid the observation that tax assessed value is not a component characteristic of a house. He cites Wickens (1972) as his justification for using assessed value as a proxy variable.[120] However, Frost (1979), Barnow (1976) ,[121] Aigner (1974) ,[122] and McDonald (1980) have identified conditions that would invalidate Wickens's results.[123] Dr. Kilpatrick fails to address these problems; nor does he perform any test to validate the use of assessed value as a proxy variable for all of the omitted variables in the Greenfield AVM.

[118] Kilpatrick Report at 43 n.122

[119] Butler, 1982, "The Specification of Hedonic Indexes for Urban Housing," Land Economics, 58:1, 96-108.

[120] Kilpatrick Report at 38 n.100.

[121] Barnow, B.S., "The Use of Proxy Variables When One or Two Independent Variable are Measured with Error," *The American Statistician*, 30, 119-121.

[122] Aigner, D.J., MSE Dominance of Least Square with Errors of Observation, *Journal of Econometrics* 2, 365-372.

[123] Frost (1979) points out that Wickens's results hold only when the measurement error embedded in the proxy variable is a random variable independent of the true explanatory variables. In addition, Barnow (1976) shows that Wickens's results do not hold when more than one independent variable (such as living area, lot size, etc.) is measured with error. Furthermore, Aigner (1974) shows that the use of a proxy variable can actually increase the mean squared error (MSE) of the estimated regression coefficients. Frost (1979) also points out that "proxy variables should not be used indiscriminately." In addition, McDonald (1980) points out that including a proxy variable to represent omitted variables can make the results *worse*. McDonald describes a test that researchers should conduct before blindly including a proxy variable in a regression analysis of housing prices.

86. Dr. Kilpatrick cites two studies that support the use of proxy variables in a hedonic model of housing prices.[124] However, the first study (Goodman & Thibodeau – 2003) says nothing about proxy variables. The second study (Clapp, Giaccoito, and Richo – 1996) uses assessed value (plus time of sale) as an explanatory variable to build an index of aggregated house prices over time. These studies do not suggest that assessed value should be used to predict the prices of individual houses. Yet, Dr. Kilpatrick cites both of these studies to support his use of assessed value as a proxy variable to predict the prices of individual houses.

87. Tax assessed values can suffer from both horizontal and vertical inequity.[125] That is, two identical houses can have different assessed values (horizontal inequity); or two houses with very different market values can have the same assessed value (vertical inequity). These inequities occur primarily because tax assessors are not always unbiased and they can and do make errors in estimating the market value of a house. In fact, if tax assessors were as thorough and complete as Dr. Kilpatrick claims in his deposition,[126] then there would be no need to include other housing characteristics in the Greenfield AVM (i.e., the Greenfield AVM would not be needed at all) because market values could be accurately measured by (some multiple of) tax assessed values. Dr. Kilpatrick's testimony contradicts his inclusion of these house characteristics in the Greenfield AVM.

88. Dr. Kilpatrick does not use retrospective tax assessed values in estimating the allegedly retrospective market values of the Subject Properties. The tax assessed values used in the Greenfield AVM are at least four years and on average 6.3 years after the date of the

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[124] Kilpatrick Report at 38, n. 100.

[125] Sirmans, G.S., Gatzlaff, D.H., and Macpherson, D.A. (2008). Horizontal and Vertical Inequity in Real Property Taxation, *Journal of Real Estate Literature*, 16:2, 167-180.

[126] Kilpatrick Nov. 13 Dep. Tr. at 104:4-107:11.

origination of the loans in this matter.[127] In Dr. Kilpatrick's deposition, he justifies the use of future tax assessed values in lieu of retrospective tax assessed values because he claims that the Greenfield AVM coefficients for days, days-squared, and tax assessed value convert future tax assessed values into a predictor of retrospective house values.[128] However, days and days-squared make adjustments for changes in market conditions between the date of the original appraisal (of the Subject Property) and the date (no more than one year earlier) of the sale of the (corresponding) regression observations. Thus, the days and days-squared coefficients are backward looking. They do not adjust for the difference between the date of the original appraisal and the date of the future tax assessed value of the Subject Property.

## VIII. Dr. Kilpatrick's Greenfield AVM Generates Irrational and Unbelievable Results

89. The concept of market value rests upon the basic theory of supply and demand, especially as expressed in the implicit markets theory articulated by Sherwin Rosen.[129] Rosen's seminal article is widely recognized as the premier authority underlying hedonic price models. Today, hedonic price models are assumed to be supported by Rosen's implicit markets theory, unless the author states otherwise. Dr. Kilpatrick identifies no particular theory to support his hedonic model, so he presumably intends it to be supported by Rosen's implicit markets theory—otherwise, it is not supported by any theory at all.

### A. Background on Implicit Markets Theory

90. Implicit markets theory decomposes the price of a durable, composite good, such as a house, into the implicit value of the good's various characteristics. A durable composite

[127] Isakson Report at 42.

[128] Kilpatrick Deposition at 126:15 to 127:18.

[129] Rosen, S. (1974), Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition, *Journal of Political Economy*, 82:1, pp. 34-55.

good lasts a long time (durable) and consists of an amalgamation of several invariant features or characteristics (composite). For example, an automobile is a durable composite good consisting of the amalgamation of many parts such as the engine, the drive train, the interior seats, the power steering, etc. Similarly, a house is a durable composite good consisting of various characteristics, such as living area, number of bathrooms, lot size, etc.

91. In simple terms, each characteristic of the composite good has an implicit price that can be estimated from housing sales data using an appropriate statistical technique. The price (or value) of the composite good (an entire house) can be expressed as the sum of the amount of each characteristic times that characteristic's implicit price.[130] Implicit markets theory can be illustrated with a simplified example. Suppose the relevant characteristics of a house consist of:

- 2,000 square feet of living area; and
- two bathrooms.

Further suppose that the implicit prices are:

- living area = $95/square foot; and
- bathrooms = $2,500/bathroom.

Then, the value of the house can be expressed as (the implicit prices are in *italics* and the amount of each characteristic is in **bold** type):

= *$95****2,000** + *$2,500****2**
= <u>$195,000</u>

92. The process of how the housing market works to yield the implicit prices is one that should be familiar to anyone who has purchased or sold a house. At its basic level, the process consists of many buyers and sellers who bargain over housing prices. The many buyers

[130] *Id.* (Technically, the hedonic equation should be non-linear, which would make the implicit prices variable. In this example, I simplify the hedonic model by using a linear equation.)

formulate bid prices that they are willing and able to pay for each characteristic of a house they would like to buy. Similarly, the many sellers formulate offer prices that they are willing and able to accept as payment for each characteristic of the house they wish to sell. Buyers try to pay the lowest house price possible, while sellers try to receive the highest house price possible. As buyers and sellers agree to sales prices for a large number of houses, the implicit price of each characteristic of the houses emerges such that the sum of the amount of each characteristic times its implicit price equals the market price of the entire house, as illustrated in the above example.[131]

93. House builders use implicit price information to decide the amount of each characteristic to bundle into the houses they build. For example, if the implicit price of an extra bathroom exceeds the cost of adding an additional bathroom to a house, builders will start adding an additional bathroom to the houses they build, and the implicit price of an additional bathroom will decline. In equilibrium, the implicit price of each characteristic should equal its cost. Housing market studies often use the implicit-price-equals-cost equilibrium condition to assess the reasonableness of the implicit prices they estimate.[132] For example, if the estimated implicit price of an extra bathroom is very high or very low (perhaps even negative), then the analyst would conclude that there is something wrong with the implicit price model being used. Indeed, a basic requirement of implicit price theory is that the implicit price of any characteristic must be greater than zero as long as that characteristic is an economic good (as opposed to an economic bad, such as a functionally obsolete kitchen or recent flood/fire damage to the house).

[131] *Id.*

[132] *Id.*

94. In hedonic theory, the characteristics of a composite good, such as a house, must also meet additional conditions.[133] First, each characteristic must be an inseparable part of the good.[134] That is, the characteristic is built into the composite good and cannot be increased, decreased, or altered except at considerable cost.[135] For example, living area qualifies as a characteristic under these criteria because it is an inseparable part of a house and it is costly to increase or decrease it. But, the light bulbs in ceiling lights, the seller's furniture, etc., are separable from the house, and would, therefore, not be considered a characteristic of the house. Second, when a characteristic of a house is properly defined, it will also be a determinant of the value of the house.[136] That is, a change in the characteristic will *cause* the value of the house to change. For example, larger houses sell for a higher price than smaller houses because living area is a determinant of the value of a house. Third, the characteristic must be valued by both buyers and sellers.[137] For example, the number of bathrooms qualifies under these criteria as a characteristic because buyers and sellers are able to place a value on an additional bathroom in a house as they bargain over the price of a house (and because bathrooms are also an inseparable part of a house).

95. To be reliable, any hedonic model of a housing market based on implicit markets theory must include features of a house that meet the test to be characteristics. Any additional explanatory variables must be justified as variables to control for something that causes the price

[133] Triplett, J.E. (1986), The Economic Interpretation of Hedonic Methods, *Survey of Current Business*, 66:1, pp. 36-40, specifies and discusses these three conditions in greater detail.

[134] *Id.*

[135] *Id.*

[136] *Id.*

[137] *Id.*

of every house to vary in a systematic manner.[138] For example, sometimes additional environmental explanatory variables are included, such as noise levels near an airport, quality of rural well water, unpleasant odors near a hog lot, etc. But, no explanatory variables should be included that cannot be justified on the basis of being a characteristic of the house or being something that systematically causes housing prices to differ.

**B. Irrational and Unbelievable Negative Coefficients**

96. The Greenfield AVM often produces regression coefficients for its housing characteristic variables that violate implicit price theory. As noted earlier, the coefficients for the housing characteristics in an implicit price model should make economic sense. To assess this requirement requires drawing a line between which coefficients do and do not make economic sense. As long as the characteristic represents a feature of the house that buyers desire, its estimated coefficient should be greater than zero. Negative coefficients for living area, lot size, year built and number of bathrooms would violate the requirement that economic goods have positive implicit prices (*i.e.*, that newer houses sell for more than older houses when interpreting the variable year built). In particular, one cannot reasonably expect an *increase* in any desirable housing characteristics to *decrease* the value of a house.

97. Table 1 lists the number and percentage of regressions where the Greenfield AVM OLS or OLSXY models have coefficients for four key house characteristics that are less than zero, making them irrational and unbelievable. Table 2 indicates the percentage of negative coefficients that are statistically significant at the 0.05 level (corresponding to 95% confidence).

[138] Epple, D. (1987), Hedonic Prices and Implicit Markets: Estimating Demand and Supply Functions for Differentiated Products, *Journal of Political Economy*, 95:1, pp. 59-80.

| Table 1: Negative Regression Coefficients in the Greenfield AVM | | |
|---|---|---|
| **Explanatory Variable** | **Negative Greenfield AVM OLS Coefficients** | **Negative Greenfield AVM OLSXY Coefficients** |
| Year Built | 30.8% (182/591) | 32.3% (191/591) |
| Living Area | 11.3% (52/460) | 9.3% (43/460) |
| Lot Size | 29.3% (185/631) | 25.7% (162/630) |
| Bathrooms | 21.7% (118/544) | 20.8% (113/544) |

| Table 2: Percent of the Negative Regression Coefficients that Are Statistically Significant | | |
|---|---|---|
| **Explanatory Variable** | **Significant Negative Greenfield AVM OLS Coefficients** | **Significant Negative Greenfield AVM OLSXY Coefficients** |
| Year Built | 79.7% (145/182) | 75.4% (144/191) |
| Living Area | 65.4% (34/52) | 53.5% (23/43) |
| Lot Size | 52.4% (97/185) | 43.8% (71/162) |
| Bathrooms | 67.8% (80/118) | 59.3% (67/113) |

98. The negative coefficients for year built are especially troublesome because they reveal that the regressions in the Greenfield AVM violate implicit price theory, which holds that older houses suffer from more depreciation than newer houses.[139] Yet 30.8% (182/591) of the OLS estimates of the implicit price of year built in the Greenfield AVM are less than zero, meaning that, according to the Greenfield AVM, the newer the Subject Property, the lower its value. Moreover, looking at Table 2 for the OLS Greenfield AVM regressions, 145 of the 182 (79.7%) negative coefficients for year built are statistically significant (at the 0.05 level). Thus, the negative coefficient for year built is critically important in explaining and predicting house

[139] Winson-Geideman, K., Jourdan, D., and Gao, S. (2011), The Impact of Age on the Value of Historic Homes in a Nationally Recognized Historic District, *The Appraisal Journal*, pp. 327-343, report that even historic houses depreciate in value with increasing age until they reach the age of 119 years, at which point the historic houses begin to increase in value.

price in 145 of the 591 (24.5%) Greenfield AVM OLS regressions. Similar patterns are seen in Tables 1 and 2 for living area, lot size, and number of bathrooms. Thus, between 9 and 33 percent of the Greenfield AVM OLS or OLSXY regressions had coefficients used to estimate the value of the Subject Properties in this case that are irrational and unbelievable. Moreover, 43 to 80 percent of these irrational and unbelievable coefficients are statistically significant. These irrational and unbelievable negative coefficients make the Greenfield AVM's estimates of the values of the Subject Properties inaccurate, imprecise, and unreliable.

## IX. Dr. Kilpatrick's Greenfield AVM Contains Systemic Statistical Flaws

99. Because Dr. Kilpatrick claims that the Greenfield AVM estimates of value are accurate[140] and precise,[141] it is appropriate to clearly define these (often misused) terms. The terms accurate and precise do not mean the same thing. Accurate means that one is, on average, hitting the bulls-eye of a target. Precision, on the other hand, deals with the tightness or spread of the individual shots. For example, in the lower left target of Figure 6, the average of the four shots is hitting the bulls-eye, since each individual shot hits the bulls-eye. The upper left target of Figure 6 has no shots in the bulls-eye, but the average of these four shots lies on the bulls-eye. So, comparing the two left-hand targets in Figure 6, both are accurate, but the shot pattern in the lower one is more precise than that in the upper one. Additionally, the shot patterns in the two right-hand targets in Figure 6 each display a pattern that is not accurate because the average shot is not hitting the bulls-eye. However, the upper right shot pattern is more precise than that for the lower right target. The lower right target in Figure 6 is the worst case scenario; the pattern is neither accurate nor precise.

[140] Kilpatrick Report at 2.

[141] *Id.* at 53 ("[m]ost of the predictions of the [G]AVM are precise.").

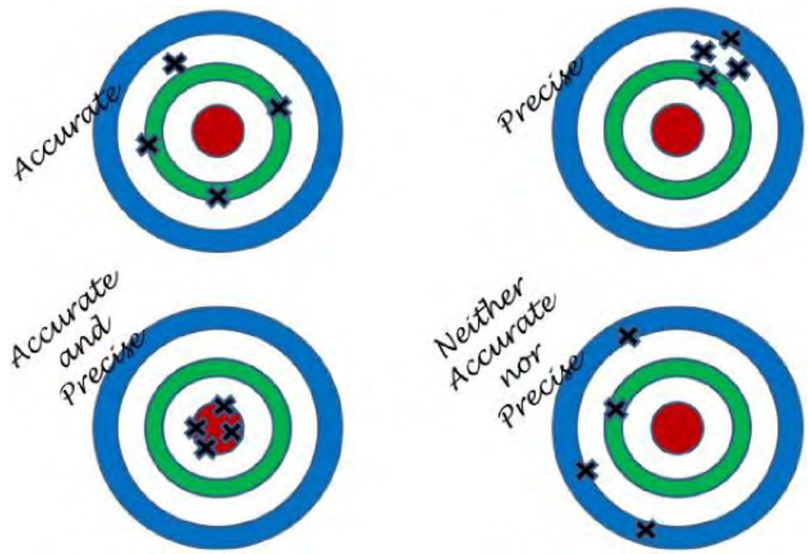


FIGURE 6: Accuracy versus Precision.

Source: msclantonsphysicalsciencepage.weebly.com/accuracy-versus-precision-lab-activity-page-two html

100. In terms of the Greenfield AVM, the individual shots in Figure 6 represent the Greenfield AVM estimates of value (*i.e.*, the sampling distribution of the Greenfield AVM estimator) for a particular Subject Property. For any particular Subject Property, the Greenfield AVM (or any other estimation model) will produce different estimates of value depending on the criteria used to select the raw data (regression observations) and methodology to process the raw data into an estimate of value. These various estimates of value are called the sampling distribution (of the Greenfield AVM).

101. In particular, the accuracy of the Greenfield AVM estimates of value must be measured by how close they come to hitting the bulls-eye, the actual sales price (market value) of the Subject Properties.[142] The Greenfield AVM estimate will be biased if it does not, on average, equal the actual sales price (market value) of the Subject Property. Statistically, the

[142] Dr. Kilpatrick claims that the "true" market value of the Subject Property is the Greenfield AVM estimate of value even when the actual sales price is known. *See* Kilpatrick Report at 63.

average or expected value of the Greenfield AVM's sampling distribution must be equal to the actual sales price (market value) of the Subject Property.

102. Biases in the Greenfield AVM are introduced by many factors, for example: using poor sampling strategies (selecting regression observations from zip codes other than that of the Subject Property) and using flawed statistical methodology (estimating the *mean* house price by using a calculation that results in the sample *median*).

103. The precision of the Greenfield AVM estimates of value must be measured by the spread of the pattern around the bulls-eye, the actual sales price (market value) of the Subject Property. Statistically, the variability of the Greenfield AVM's sampling distribution is a measure of the precision of the Greenfield AVM. The precision of the Greenfield AVM is artificially improved by using the Cross-Validation Filter (discussed above) to remove regression observations for which the Greenfield AVM does not predict the actual sales price very well.

104. The choices made in the selection of the regression observations and methodology determine the accuracy and precision of the Greenfield AVM estimates of value. Poor choices, such as the theoretical or methodological flaws in the Greenfield AVM detailed below, will result in a "neither accurate nor precise" pattern similar to that in the lower right portion of Figure 6.

### A. Dr. Kilpatrick Uses an Improper Level of Statistical Significance

105. Dr. Kilpatrick's foundational opinion, that the original Subject Properties' appraised values are significantly higher (by 8.92%) than the Greenfield AVM estimates, fails to meet the standards of scientific evidence. The scientific standard for judging statistical significance is far higher (95%) than that used by Dr. Kilpatrick (68.27%) in rendering his

foundational opinion.[143] Dr. Kilpatrick clearly states that he "concluded that the original appraised values of 208 of the 672 sample Nomura properties . . . are *significantly* higher than the Greenfield AVM appraised values, rendering the original appraised values inaccurate."[144]

106. Specifically, Dr. Kilpatrick formally tests the null hypothesis that the Greenfield AVM reconciled value is statistically the same as the appraised value for each Subject Property. Because Dr. Kilpatrick uses a decision rule of one FSD,[145] he is conducting a hypothesis test with a corresponding significance level of 0.3174 (error rate).[146]

107. Dr. Kilpatrick reports that he measures statistical significance, when comparing the appraised value to its corresponding Greenfield AVM estimate for each of the Subject Properties, by conducting a two-sample t-test.[147] The first sample consists of 672 differences between the Greenfield AVM reconciled value and the original appraisal of the Subject Properties. The second sample consists of the differences between the Greenfield AVM reconciled value and the selling prices for more than 1.5 million CoreLogic sales. Not only does Dr. Kilpatrick make an "apples-to-oranges" comparison of the Greenfield AVM reconciled values (*i.e.*, comparing to appraised values in one sample versus comparing to selling prices in the other), the CoreLogic sales have been artificially filtered (*i.e.*, using only the middle 30th

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[143] *See* Kilpatrick Report at 62.

[144] Kilpatrick Report at 4 (emphasis added). An effect is considered statistically significant, not only because it is important, but because it can be shown that the effect is unlikely to occur merely by chance. The probability that an effect has occurred merely by chance is called the p-value. A p-value of 0.05 is considered the maximum standard for statistical significance in practice. *See* Sirkin, R. Mark (2005), *Statistics for the Social Sciences, 3rd Edition*, Thousand Oaks, CA: SAGE Publications, Inc., pp. 271–316.

[145] Kilpatrick Report at 63-64, 67. If the original appraisal is more than 15.1% (one FSD) higher than the Greenfield AVM reconciled value, then Dr. Kilpatrick declares this Subject Property's original appraisal to be "significantly higher" or substantially overvalued.

[146] In other words, Dr. Kilpatrick has a 31.74% chance of concluding that an original appraisal is substantially overvalued when it, in fact, is not overvalued.

[147] Kilpatrick Report at 63.

percentile and removing errors greater than 100%), while the appraisals of the Subject Properties have not. Dr. Kilpatrick artificially filters the largest errors out of the CoreLogic sales data, but not out of the 306 appraisals of the Subject Properties. Dr. Kilpatrick's conclusion that "there was a systemic difference between the Nomura sample appraisals and those of the general stock of U.S. property values"[148] is not supported because he filters one dataset but not the other.

108. Statistical regression theory dictates that if the post-CV filtered dataset (the distribution of the regression observations to be used in the Greenfield AVM) is normally distributed, then the sampling distribution of the Greenfield AVM's OLS and OLSXY predicted values, when properly standardized, will exactly follow a t-distribution.[149] Furthermore, because each Greenfield AVM regression uses at least 100 observations, a normal distribution will approximate the t-distribution for the sampling distribution of the Greenfield AVM reconciled values.[150] As a result, when the post-CV filtered regression observations used to produce a Greenfield AVM predicted value are normal, the appropriate (95%) confidence interval for the Greenfield AVM predicted value is given by: Predicted value +/- 1.96 times the FSD of the predicted value. Correspondingly, any two-tailed hypothesis test using a Type I error probability (significance level) of 0.05 will require +/- 1.96 as cutoff values.

109. By using a one FSD criterion to judge significance, Dr. Kilpatrick is using the confidence interval given by:

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[148] *Id.*

[149] Neter, *et al.*, *supra* note 58, at sec. 6.7.

[150] The Greenfield AVM reconciled values' sampling distributions will be approximately normal because (i) a t-distribution converges to a standard normal distribution as the sample size increases; Ott, R.L. and Longnecker, M. (2010), *An Introduction to Statistical Methods and Data Analysis,* 6th Ed., Brooks/Cole, ch. 6, at 251; and (ii) the Greenfield AVM is a linear combination (weighted average) of the OLS and OLSXY predicted values. Linear combinations of normal random variables are normally distributed; Rencher, A.C. and Christensen, W.F. (2012), *Methods of Multivariate Analysis, 3rd Edition*, New York: John Wiley and Sons, Inc., pp. 94-95.

Predicted value +/- 1 times the FSD of the predicted value.

This interval has a confidence level of only 68.27% (a significance level of 0.3173) for testing whether or not the Greenfield AVM estimate is statistically the same as the appraised value whenever the Greenfield AVM's post-CV filtered regression observations are normally distributed.[151] Dr. Kilpatrick's opinions using a significance level of 0.3173 are scientifically insupportable because 0.3173 is over six times greater than the maximum standard (0.05) set by the *Reference Manual on Scientific Evidence*[152] and justified as a criterion for statistical significance by Cowles and Davis (1982).[153] In claiming that the Greenfield AVM does not do hypothesis testing,[154] Dr. Kilpatrick conveniently avoids admitting that he is using an insupportably low confidence level (68.27%). However, in direct contradiction to his claim that he does not do any hypothesis testing, Dr. Kilpatrick opines that 208 of the original 672 appraised values are significantly overvalued.

110. When Dr. Kilpatrick finally uses the appropriate statistical metric, a 95 percent confidence interval, his opinion that the original appraised values are still "substantially overvalued"[155] is flawed for two reasons. First, Dr. Kilpatrick does not compare the Greenfield AVM estimates to the best indicator of market value, the actual sales prices of the Subject Properties. Second, Dr. Kilpatrick's cross-validation filter (discussed above) so drastically reduced the variability in the Greenfield AVM (a more than six-fold decrease) that the FSD he

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[151] As discussed below, the post-CV filtered regression observations for 480 of the 672 (71.4%) Greenfield AVM OLS and 516 of the 671 (76.9%) Greenfield AVM OLSXY models were normally distributed for the Subject Properties.

[152] According to Federal Judicial Center, Reference Manual on Scientific Evidence, p. 320, "the level of statistical significance . . . is set conventionally at 0.05."

[153] Cowles, M. and Davis, C. (1982), "On the Origins of the .05 Level of Statistical Significance," *American Psychologist*, 37:5, pp. 553-558.

[154] Kilpatrick Feb. 13, 2014 Dep. at 246:23-250:15.

[155] Kilpatrick Report at 73-74.

uses is artificially low, rendering any resulting confidence intervals artificially too narrow. Had Dr. Kilpatrick calculated this confidence interval correctly, his opinion that 14.1 percent of the Subject Properties are "substantially overvalued" would not be supported by his own model.[156]

111. Dr. Kilpatrick claims that he "corrected" the confidence intervals in a supplemental report he filed in this case, and that this establishes his opinions at a 95% confidence interval. He does so by calculating the FSD of each individual regression (rather than the global .151 FSD of the model) to construct his 95% confidence intervals. However, the same flaws still exist—Dr. Kilpatrick continues to ignore sales prices, and continues to use the post-cross-validation filtered data to construct the FSDs. As long as those flaws remain, the FSDs will be artificially low.

112. As a result, not only are the Greenfield AVM's individual estimates of house value inaccurate, imprecise, and unreliable, but its critical decision rule, used to conclude that the appraised value is significantly higher than its corresponding Greenfield AVM estimate, is based upon an unjustifiably low 68.27% confidence level.

### B. Dr. Kilpatrick's Greenfield AVM Incorrectly Calculates House Values Because of a Back-Transformation Error

113. As described in this section, the Greenfield AVM incorporates what statisticians call a "back-transformation error," which causes the Greenfield AVM's results to systematically understate house values. When someone is considering selling his or her house, there is a range of possible prices at which the house will actually sell. This range of possible prices (in dollars) is skewed to the right, as are most distributions of monetary prices. This right skewness is due to the fact that there is a lower limit on price (*i.e.*, zero) but no upper limit on price. Figure 7 shows

[156] Kilpatrick Report at 73-74.

what a typical right skewed distribution, such as housing prices, looks like. The dollar prices are on the horizontal axis, while the frequency with which each possible price might occur is on the vertical axis. The long tail on the right-hand side shows that there is no upward limit on possible prices, while the short tail on the left-hand side shows that the lowest possible price of any house, in theory, is zero.

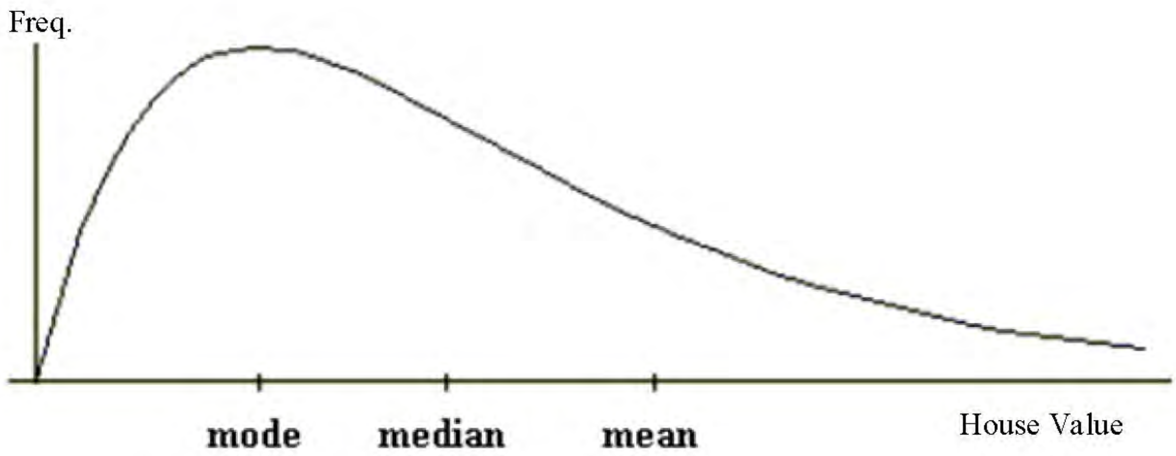


Figure 7: A Right Skewed Distribution

114. Notice in Figure 7 that, for right skewed data, the mean is greater than the median which is greater than the mode. The *mean* is simply the average or expected price. Half of the possible prices are greater than and half are less than the *median* of the possible prices. The *mode* is the most frequently occurring possible price. This skewed distribution of possible prices is problematic for OLS regressions, such as those used in the Greenfield AVM.

115. The easiest way to deal with this problem is to transform the sales prices into a variable that is more symmetrically distributed. The transformation that most real estate analysts, and the Greenfield AVM, use is to transform price in dollars into the natural logarithm of price. Once this transformation is performed, the distribution of the log of prices looks more like Figure 8 below. Now the horizontal axis represents the natural logarithm of price, while the vertical axis continues to represent the frequency with which each (log of) price occurs.

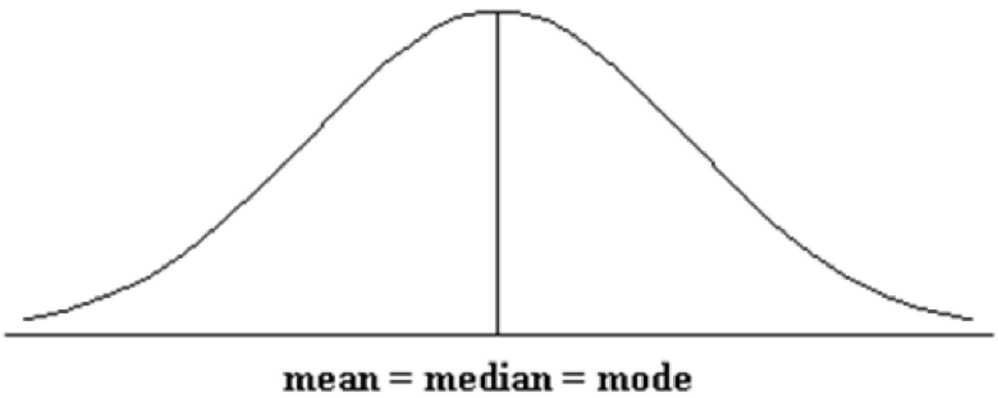


Figure 8: A Symmetrical Distribution

116. For symmetrical distributions with a single peak or mode, such as that above, the mean, median, and mode are all the same amount (*i.e.*, the average log of price).

117. The Greenfield AVM does not directly estimate market value in dollars. Instead, it estimates the natural logarithm of the market value of a Subject Property, which is then back-transformed into a dollar amount by simply raising the base of the natural logarithm, *e*, to the power of the estimated log of price.[157] For example, a Greenfield AVM estimate of the value of a Subject Property, such as 12.3239 on the log scale, is back-transformed into $225,010.[158] The problem with using this simple back-transformation is that it yields the *median*, not the mean, on the dollar scale. That is, the back-transformed mean on the *log scale* does *not* equal the mean or expected price on the *dollar scale*. In fact, the back-transformed mean estimated by the Greenfield AVM will *always* be less than the expected price of each Subject Property.[159]

118. Because of this systemic methodological error, the Greenfield AVM has a built-in bias that yields an estimate of the market value (in dollars) that is *systematically less* than the

[157] *See* Kilpatrick Report, Appendix 5-1, at 34.

[158] $e^{12.3239}$ = $225,010.

[159] *See* Hippel, P.T. (2005), Mean, Median, and Skew: Correcting a Textbook Rule, *Journal of Statistics Education*, 13:2.

expected market value (in dollars) of all of the Subject Properties, rendering the Greenfield AVM estimates of value inaccurate, imprecise, and unreliable.

### C. Dr. Kilpatrick's Greenfield AVM Violates Assumptions of the OLS Technique

119. When using the OLS technique, it is important to examine the results carefully to make sure that *all* of the assumptions underlying the technique hold. Some of these assumptions can be tested empirically, while others are assessed in different ways discussed below. For example, the explanatory variables of an OLS model must be important in explaining the dependent variable. Changes in the explanatory variable must cause the dependent variable to change. Also, the direction and magnitude of the change must be consistent with the theory underlying the OLS model. The technique and its assumptions are discussed in more detail below.

#### 1. Ordinary Least Squares Technique

120. The OLS or ordinary least squares technique, sometimes called a regression analysis, is a statistical method used to predict and explain the relationship between a dependent variable, such as the price of a house, and one or more independent (or explanatory) variables that are hypothesized to explain the dependent variable. This relationship is expressed as an equation, such as:

$$Y = a + bX_1 + cX_2 + \varepsilon$$

where $Y$ = the dependent variable, such as price of a house

$X_1$ = an independent variable, such as living area

$X_2$ = another independent variable, such as number of bathrooms

$a$ = intercept term, one of the coefficients to be estimated

$b,c$ = slope terms, additional coefficients to be estimated

$\varepsilon$ = an error term recognizing that the equation will not be perfect.

121. We can have multiple independent variables (the Xs) in the above equation, but only one dependent variable (Y).

122. The OLS technique is often used to "fit" a line to a set of data. We can illustrate the technique with the simple graph in Figure 9 that depicts only one independent variable.

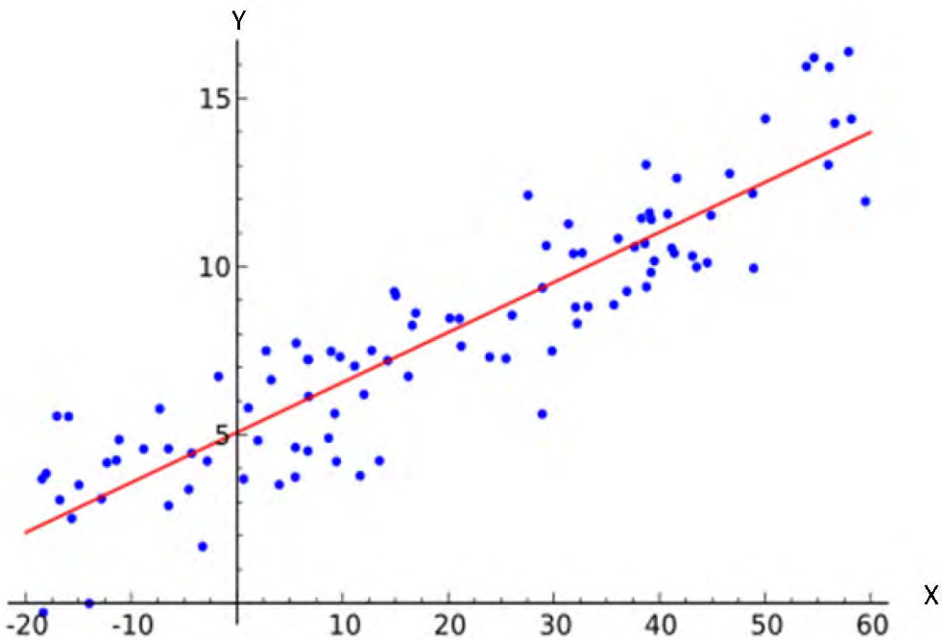


Figure 9: A Simple Linear Regression Line with Hypothetical Data

123. In Figure 9, the vertical axis (Y) represents the dependent variable, while the horizontal axis (X) represents the independent variable. Notice that the OLS line lies very near the center of the data points. Also notice that many of the points do not lie exactly on the OLS line. The vertical distance between the OLS line and any data point is the error term (called ε in the equation above). Each observation (the dots in Figure 9) has an error associated with it.

124. Estimates of the coefficients (a, b, and c in the equation above) should be what are called *best*, *linear*, *unbiased*, *estimators* ("BLUEs"). *Best* means that no other set of coefficients will be as precise as the ones we have estimated (*i.e.*, any other set of coefficients – any other line in Figure 9 – will produce a greater sum of the squared errors). *Linear* means that the sales

price must be expressed as a linear combination of explanatory variables as illustrated in the equation above. *Unbiased* means that the coefficients are not biased in any particular direction. *Estimators* simply refers to the fact that the coefficients are estimates of the true parameters. It is this BLUE property of the OLS technique that makes it so popular, especially in housing market studies. As long as the data being analyzed satisfy the assumptions of the OLS technique, the OLS estimates are better (*i.e.*, accurate *and* more precise) than any other (linear) estimates because the OLS technique is guaranteed to yield the *best, linear, unbiased, estimators* possible.[160] There are other statistical techniques, such as ridge or least absolute deviation regressions that might be more appropriate when the OLS regression assumptions are violated.[161]

125. The OLS technique provides these BLUEs only if data being analyzed satisfy the assumptions underlying the OLS technique. The OLS technique calculates the BLUEs by using the error term (ε) above. Specifically, the technique finds the coefficients that minimize the sum of the squared error terms. This is where the term "least squares" comes from. That is, given any particular set of possible coefficients, the technique first calculates the error term, then it squares the error term, and then it adds up all of the squared error terms (one for each observation). The coefficients that minimize the sum of these squared errors are the BLUEs.[162]

126. The OLS technique can produce powerfully erroneous explanations and predictions when it is applied to data that violate its underlying assumptions. A user of the OLS

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[160] Mirer, T.D. (1995), *Economic Statistics and Econometrics, Third Edition*, New Jersey: Prentice Hall, p. 287; *see also* Neter, et al., *supra* note 58, at 20-21 for a discussion of the Gauss-Markov theorem, which states that the OLS estimators are unbiased and have minimum variance among all unbiased, linear estimators.

[161] *See* Phillips, R.F. (1997), On the Robustness of Two Alternatives to Least Squares: A Monte Carlo Study, *Economic Letters*, Volume 56, pp. 21-26 for a discussion of alternatives to the OLS technique.

[162] Mirer, *supra* note 160, at 287.

technique should never rely on the results of an OLS regression without checking to make sure its assumptions are satisfied by the data.[163]

127. The standard assumptions of any OLS regression include:[164]

- The error term of the model is normally distributed.[165] The normality assumption implies that for a given set of explanatory or independent variables, the potential sales prices of a house are normally distributed. Normality is tested using a standard Pearson correlation coefficient for the residuals and their corresponding normal scores.[166] The greater the correlation coefficient value, the more likely the data-set is normally distributed. Specifically, given the large number of observations in the Greenfield AVM regressions, this correlation must be at least 0.987 to support the claim, with a 95% degree of confidence, that the error terms are normally distributed.[167]

- The error term of the model has mean zero and constant variance. The process of minimizing the sum of the squared errors of the model assures that the mean of the observed error terms will be zero. Non-constant variance, called heteroscedasticity, is often found in housing sales data and means that the variability in housing prices is related to the magnitude of the independent variables. In particular, heteroscedasticity, or the lack of constant variance of the residuals, would be indicated if the sales prices display increased (or decreased) variability as the price of the houses increases. The Breusch-Pagan test is used to formally test for constant variance of the residuals.[168] In order to pass the test of no heteroscedasticity, there should be no relationship between squared residuals and any of the explanatory variables. If the p-value for the Breusch-Pagan test statistic for heteroscedasticity is below 0.05, then heteroscedasticity exists and the assumption of constant variance is violated.

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[163] Isakson, H.R. (2001), Using Multiple Regression Analysis in Real Estate Appraisal. *The Appraisal Journal*, October, 424-430.

[164] For a full discussion of these assumptions and their implications, *see* Neter, *et al.*, *supra* note 65; Ott and Longnecker, *supra* note 150; Seber, G.A.F. (1977), *Linear Regression Analysis*, Wiley, Weiss, N.A., (2008), *Introductory Statistics, 8th Edition*, Addison Wesley.

[165] Normality is not required to fit an OLS regression (estimate coefficients, create predicted value, create residuals, etc.). Normality is required for correct statistical inference in certain analytical settings.

[166] Looney, S.W. and Gulledge, T.R. (1985), Use of the Correlation Coefficient With Normal Probability Plots, *The American Statistician*, 39:1, pp. 75-79.

[167] *Id.*

[168] Neter, *et al.*, *supra* note 65, at sec. 3.6.

- The errors are independently distributed. Housing sales data typically contain spatially dependent error terms because urban areas consist of multiple neighborhoods within which houses are similar, but between neighborhoods houses can be very different. Specifically, spatial correlation (geographic clustering of the error terms) means that two houses with comparable housing characteristics might be more similar in price if they are physically located near each other (than if they were farther apart). Spatial correlation models rely on distances between houses, in contrast to a trend surface model which models the effect of location on house prices directly using some function of the x, y coordinates of each house as explanatory variables. (The Greenfield AVM OLSXY regressions are trend surface models.) Trend surface models do not necessarily account for the presence of spatial correlation.

- Spatial correlation is detected by visually inspecting a special kind of graph called a variogram.[169] A variogram displays the relationship between a measure (gamma) of the variability of the prices of a pair of houses and the distance between that pair of houses. A data-based or an empirical variogram (such as that shown in Figure 10) that displays an increase in variability between a pair of houses as the distance between the houses increases is indicative of the presence of spatial correlation. In other words, Figure 10 indicates that the variability (Y-axis) between pairs of houses is smaller as distances between the pairs of houses (X-axis) gets smaller. The downward trend in the variogram near the origin (where houses are very close together) is indicative of spatial correlation. In the presence of spatial correlation, such as that seen in Figure 10, the OLS estimates become imprecise and unreliable.

[169] *See* Cressie, N. (1993), *Statistics for Spatial Data*, Wiley, for a discussion of the use of variograms in the detection of spatial correlation and regression analysis of spatial data.

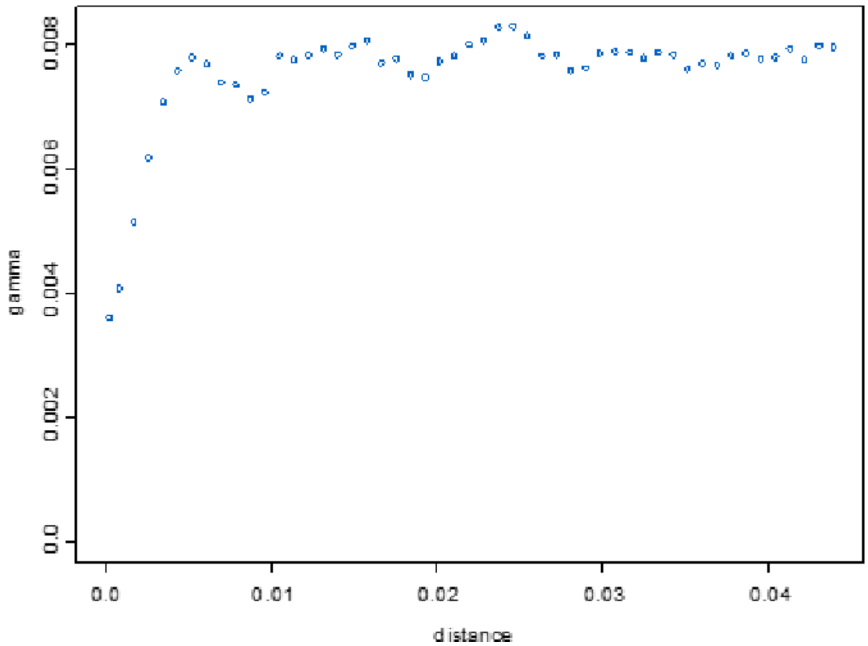


Figure 10: A Variogram Showing Spatial Correlation

- Spatial correlation is very common in housing price data because subdivision rules and builder practices tend to cluster similar houses close to each other. It is this clustering that often produces spatial correlation in housing sales data.

- An empirical variogram, such as that in Figure 11, that displays little or no change in the variability between the prices of a pair of houses as the distance between the houses increases indicates that the data-set is not spatially correlated. Notice that the data points in Figure 11 do not display any sort of upward or downward trend. Instead, the data appear to fluctuate around a horizontal line. The pattern of data points in Figure 11 are desirable because they indicate that the OLS estimates are not distorted by the presence of spatially correlated data.

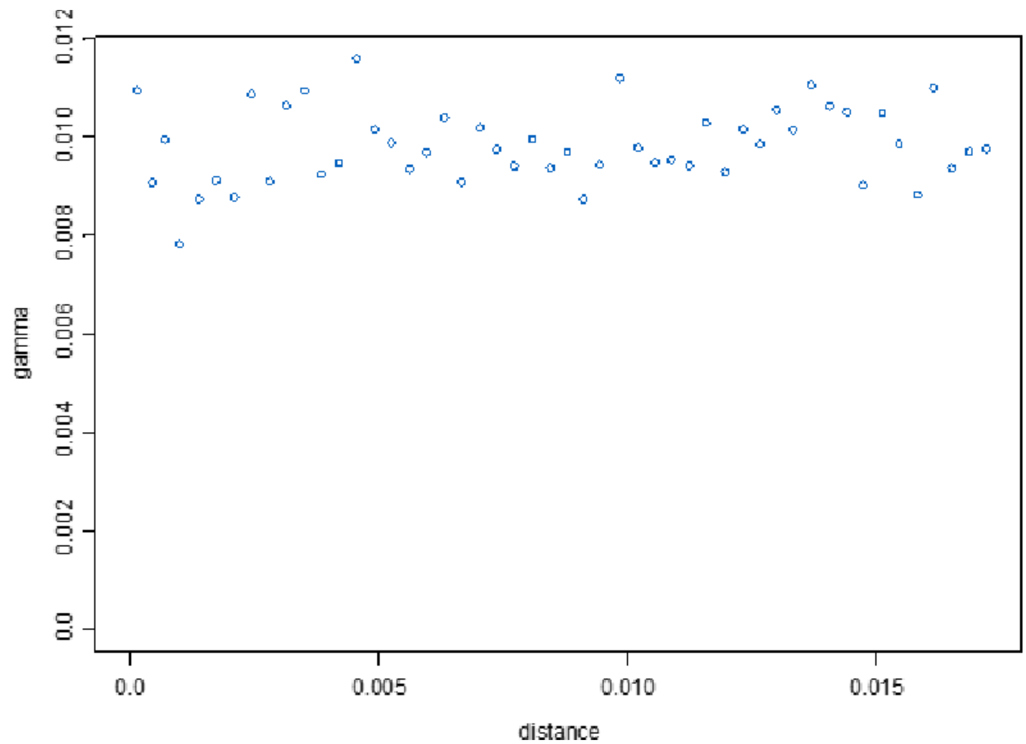


Figure 11: A Variogram Showing No Spatial Correlation

- Spatial correlation of the regression observations used in the Greenfield AVM is evaluated by constructing an empirical variogram for the OLS and OLSXY regressions' residuals for all Subject Properties. When spatial correlation is present, as shown in Figure 10, then the analyst should use a Geostatistical[170] model that accounts for spatially correlated data.

- The independent variables do not display multicollinearity.[171] When the explanatory variables are highly correlated, either direct pairwise correlations or linear combinations of each other, then multicollinearity exists. When multicollinearity is severe, estimates for relevant explanatory variables can be mistakenly deemed insignificant. In extreme cases of multicollinearity, parameter estimates might not even be produced, *i.e.*, some or all of the

[170] *Id.*

[171] Multicollinearity occurs when two or more of the explanatory variables in a hedonic model are highly correlated. In the presence of multicollinearity, the estimated coefficients become highly unstable and unreliable as estimates of implicit prices. For example, suppose we would like to explain a baseball player's runs batted in (RBIs) as a function of a player's total number of hits during the year (X1), his total at bats (X2), and his batting average (X3). If we regress RBIs (Y) on X1, X2, and X3, we would have perfect multicollinearity because X1 and X2 can be combined to exactly equal X3 (X3 = X1/X2). Accordingly, having any two of the three explanatory variables determines the third. This third variable is, therefore, redundant information and, as such, should be eliminated from the regression model. The relationship between the explanatory variables does not have to be exact for multicollinearity to be a problem. But, if the relationship between combinations of the explanatory variables is sufficiently correlated, then multicollinearity exists.

regression parameter estimates will be blank or missing. The Variance Inflation Factor ("VIF") can be used to test for the presence of multicollinearity.[172] If the VIF value is larger than 10,[173] then multicollinearity exists. Multicollinearity can be mitigated by removing redundant variables and/or standardizing variables before creating higher order polynomials (for example, standardizing days in the Greenfield AVM's OLSXY model before subsequently squaring it).

- The independent variables are fixed effects (measured without error), meaning that their exact values are measured precisely (such as square footage, number of bathrooms, lot size, time of sale, etc.). Most housing characteristics satisfy this requirement. But housing data can contain entry errors, and the analyst must deal with these errors. A common method to deal with data entry errors is to correct the errors by checking the original source of the data to find the correct values or simply eliminate observations that contain them.

- Each observation is equally reliable. For example, if housing sales data comes from more than one source, the quality of the data can vary from one source to another. In addition, older sales may be influenced by market forces that no longer exist, making them less useful in predicting house values in the present. Better quality data should be given more weight than lesser quality data, using a weighted least squares technique.

- The independent variables have a linear relationship in explaining or predicting the dependent variable. When the basic relationship is not linear, the analyst must transform the basic relationship into a linear form or add additional terms. Analysts often use the logarithm of some of the variables to transform a fundamentally non-linear relationship into a linear relationship. If the relationship between the variables cannot be expressed as a linear relationship, then the OLS technique should not be used, and the analyst should consider some other statistical technique to explain and predict house prices.

- The regression includes only relevant explanatory variables and no relevant explanatory variables are omitted. Technically, this assumption addresses two requirements: (i) each explanatory variable contributes to explaining the value of a house; and (ii) there are no relevant explanatory variables missing from the model. Housing sales data often suffer from the problem of missing variables because the source of the data may not have collected all of the important explanatory variables. Critically important characteristics of any house includes lot size, living area, number of bathrooms, number of

[172] Neter, *et al.*, *supra* note 65, at sec. 9.5.

[173] *Id.* at 409.

bedrooms, year built, garage size, etc. All of these characteristics plus many more are routinely collected by real estate agents when listing a house for sale.

### 2. Violations of the OLS Technique Assumptions

128. Dr. Kilpatrick's opinion rests, in part, upon the OLS assumptions he used for the regressions run by the Greenfield AVM. The 672 individual Greenfield AVM OLS regressions and 671 Greenfield AVM OLSXY regressions were replicated to examine the reliability and accuracy of the OLS assumptions. As discussed below, this analysis revealed several serious violations of the OLS assumptions.

129. For each of the OLS and OLSXY regressions run by Dr. Kilpatrick, the following diagnostic statistics were gathered:

- The number of regression observations (between 100 and 2,000) selected by the Greenfield AVM before and after applying the CV=.25 filter.
- The square root of the MSE of the Greenfield AVM regressions (both OLS and OLSXY) before and after applying the CV=.25 filter.
- Individual regression parameter estimates and corresponding p-values for the post-filtered Greenfield AVM regressions.
- The VIF of the pre- and post-filtered Greenfield AVM regressions.
- The test for the residuals being normally distributed for the post-filtered Greenfield AVM regressions.
- Tests for constant variance (homoscedasticity) of the error term for the post-filtered Greenfield AVM regressions for the following independent variables: Log-scaled Assessed Value, Days, Square Feet, Year Built, Lot Size and Number of Bathrooms (when available).
- A check for spatial correlation for the post-filtered Greenfield AVM regressions— inspection of the empirical variograms constructed from Dr. Kilpatrick's OLS and OLSXY model residuals.

130. The results of these diagnostic tests are summarized in Table 3. *All* of the Greenfield AVM OLS regressions suffer from multicollinearity, 28.6% contain non-normal data, 17.1% lack constant variance for days, 34.2% lack constant variance for lot size, 40.1% exhibit

heteroscedasticity for the number of bathrooms, 42.6% lack constant variance for the living area square footage, 44.6% lack constant variance for the log of assessed value, and 53.0% lack constant variance for year built. Lastly, 74.4% of the Greenfield AVM OLS regressions suffer from spatial correlation.

**Table 3: Summary of OLS Assumptions Violations for All Subject Properties**

| OLS Assumption Violation | Greenfield AVM OLS Regressions | Greenfield AVM OLSXY Regressions |
|---|---|---|
| Lack of Normality | 28.6% (192/672) | 23.1% (155/671) |
| Heteroscedasticity - Assessed Value | 44.6% (300/672) | 41.0% (275/671) |
| Heteroscedasticity - Days | 17.1% (115/672) | 14.6% (98/671) |
| Heteroscedasticity - Year Built | 53.0% (313/591) | 51.4% (304/591) |
| Heteroscedasticity - Living Area | 42.6% (196/460) | 38.5% (177/460) |
| Heteroscedasticity - Lot Size | 34.2% (216/631) | 33.7% (212/630) |
| Heteroscedasticity – Bathrooms | 40.1% (218/544) | 36.0% (196/544) |
| Multicollinearity | 100% (672/672) | 100% (671/671) |
| Spatial Correlation | 74.4% (500/672) | 61.1% (410/671) |

131. The diagnostic tests reveal that (i) multicollinearity, (ii) heteroscedasticity in the use of the log of assessed value and year built as explanatory variables, and (iii) spatial correlation are the three most serious violations of the OLS regression assumptions. Multicollinearity can be attributed to the use of the days and days-squared in the Greenfield AVM OLS model. Dr. Kilpatrick's choice to use the log of assessed value and year built as explanatory variables induces considerable heteroscedasticity into the Greenfield AVM OLS regressions, rendering their predicted values scientifically unreliable.

132. Multicollinearity is such a serious problem in the Greenfield AVM OLSXY model that it produces no coefficients for some of its trend surface variables. After standardizing

the latitude, longitude and days variables, the standardized OLSXY model[174] had only 74 of the 671 (11.0%) regressions display multicollinearity. However, even after standardization, the Greenfield AVM still contains numerous serious errors, discussed in the next paragraph, that render its results imprecise and unreliable.

133. Similar to the OLS model results, the diagnostic tests reveal two additional serious violations of the OLSXY regression assumptions in the form of (i) heteroscedasticity associated with the log of assessed value and year built as explanatory variables and (ii) spatial correlation. The spatial correlation problem remains a serious problem because it persists even after the Greenfield AVM includes trend surface explanatory variables in the OLSXY model. Thus, the Greenfield AVM trend surface model does not account for distances between houses, as Dr. Kilpatrick claims.[175]

134. Not one of the 672 OLS and 671 OLSXY regressions performed by the Greenfield AVM passed all nine diagnostic tests identified in Table 3, primarily because all of the Greenfield AVM regressions contained multicollinearity problems. In addition, heteroscedasticity and spatial correlation are common problems. These issues completely undermine the OLS and OLSXY models and make their conclusions unreliable.

[174] To assess the impact of multicollinearity, I standardized the latitude and longitude (and days) variables for the Subject Properties and their corresponding comparable sales. I replicated the Greenfield AVM OLSXY regressions using the corrected – standardized variables (called the "Standardized Trend Surface Model"). Standardizing a variable transforms it to have a mean of zero and a standard deviation of 1. Standardizing variables gives them similar scales and helps to eliminate the multicollinearity produced when using second-order terms in an OLS regression.

[175] Kilpatrick Report at 40.

### D. Dr. Kilpatrick's Greenfield AVM Incorrectly Calculates Trend Surface Coefficients

135. The Greenfield AVM's predicted values are further compromised by the miscalculation of the second-order, or "trend surface" variables of latitude-squared, longitude-squared, and latitude times longitude. Trend surface variables can be highly collinear, especially when they are measured on a very different scale than the rest of the explanatory variables in the model and they have relatively low variances. Multicollinearity among the explanatory variables of a regression means that some of the explanatory variables are or can be predicted by the other explanatory variables. As a result, the coefficients of these second order trend surface explanatory variables become difficult to estimate. This is why the Greenfield AVM fails to estimate the coefficients of 56.6% of the second-order variables. When this problem occurs, the simplest resolution is to standardize the latitude and longitude variables before calculating the second-order terms, and then use the five new variables instead of the original five variables in the regression.[176]

136. Missing second-order coefficients for the latitude and longitude variables is not a trivial matter. Of the 671 Greenfield AVM OLSXY regressions examined, 380, or 56.6%, had at least one second-order trend surface coefficient missing. Had Dr. Kilpatrick standardized the latitude variable, the longitude variable, and the days variables before calculating the latitude squared, longitude squared and latitude-longitude interaction terms, these coefficients would not have been missing in the Greenfield AVM. (The days-squared variable did not have a problem with missing coefficients.)

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[176] *See* Legendre, P. and Legendre, L. (1998), *Numerical Ecology, 2nd Edition*, Elsevier Science, Sections 10.3.4 and 13.2.1, for further discussion of the normalization of Cartesian coordinates when estimate surface-trend coefficients.

137. If any missing coefficient is relevant for prediction, the predicted value will be incorrect. To assess the magnitude of this error, I standardized the latitude and longitude (and days) variables for the Subject Properties and their corresponding comparable sales. I replicated the Greenfield AVM OLSXY regressions using the corrected – standardized variables (called the "Standardized Trend Surface Model"). I compared the predicted values obtained by using the standardized variables to the predicted values from the Greenfield AVM. The largest discrepancy of $1,332,904 occurred for NHELI_2006_FM1_2002119369, where Dr. Kilpatrick reports a Greenfield AVM OLSXY predicted value for this property of $1,496,987. In contrast, the Standardized Trend Surface model (using standardized latitude and longitude variables in the Greenfield AVM OLSXY model) produces an estimate of house value of $164,083. For NHELI_2006_FM1_2002119369, the Greenfield AVM trend surface model reports two missing coefficients (for longitude squared and for the latitude-longitude interaction). These two missing Greenfield AVM coefficients for NHELI_2006_FM1_2002119369 play a statistically significant role in determining the estimated value of the Subject Property.[177] Thus, these two coefficients should not have been reported as missing, because they are strongly significant in predicting house prices. To illustrate further the poor performance of the Greenfield AVM for this [redacted] Subject Property, the tax assessed value is $[redacted], and its appraised value is $[redacted], yet the Greenfield AVM reconciled value for this house is $1,969,100.

138. The Greenfield AVM OLSXY estimates contain systemic methodological errors whenever the model omits a statistically significant trend surface variable. For the 291 Subject

[177] The coefficient on the square of longitude in the Standardized Trend Surface model for NHELI_2006_FM1_2002119369 is 0.5709 and has a p-value less than 0.0001; the coefficient on the interaction of latitude and longitude is 0.5723 with a p-value less than 0.0001.

Properties (43.4% out of the 671 Subject Properties) for which the Greenfield AVM reports all trend surface coefficients, its predicted values agree exactly with the predicted values obtained by properly standardizing latitude and longitude. However, for the remaining 380 Subject Properties (56.6% of the 671 total Subject Properties), where the Greenfield AVM reports at least one missing trend surface coefficient, the predicted house values obtained by using standardized latitude and longitude variables differ from those of the Greenfield AVM by a mean absolute error (MAE) or average absolute difference of $8,770.

139. The 12 largest individual prediction estimate errors generated by the Greenfield AVM for the 671 Subject Properties are listed in Table 4. Moreover, 294 of the 380 (77.4%) Subject Properties that had at least one missing OLSXY coefficient in the Greenfield AVM had an absolute error (in comparing the Standardized Trend Surface OLSXY Model estimates to that produced by the Greenfield AVM OLSXY model) of more than $1,000. In other words, if all 380 values were listed in Table 4, then 295 (77.4%) would have an absolute price difference greater than $1,000.

**Table 4: Largest Absolute Errors Between the Standardized and Greenfield OLSXY Estimate**

| Global Loan Number | Absolute Difference (in Dollars) |
|---|---|
| NHELI 2006 FM1 2002119369 | 1,332,904 |
| NHELI 2006 FM2 2002233153 | 81,687 |
| NAA 2005 AR6 1001904838 | 73,086 |
| NHELI_2007_1_2002018499 | 71,588 |
| NAA 2005 AR6 1001831520 | 61,168 |
| NHELI 2006 HE3 2001918073 | 44,643 |
| NAA 2005 AR6 1001833854 | 42,672 |
| NHELI 2006 FM1 2001901910 | 38,358 |
| NHELI_2006_FM2_2002235492 | 34,223 |
| NHELI 2007 1 2002236636 | 29,519 |
| NHELI 2006 FM2 2001839996 | 25,285 |
| NHELI 2006 HE3 2001914961 | 25,206 |

140. Based on the above analysis of the 671 Subject Properties, the Greenfield AVM OLSXY model should have produced a different estimate 56.6% of the time because 380 of the 671 Subject Properties were missing at least one trend surface coefficient. The Greenfield AVM OLSXY predicted value for these 380 properties is incorrect. Accordingly, the Greenfield AVM OLSXY estimates are scientifically unreliable because they produce erroneous estimates 56.6% of the time.

141. Dr. Kilpatrick fails to correctly employ recognized statistical techniques when he fails to standardize the trend surface variables in the Greenfield AVM OLSXY regressions.[178] This error causes the Greenfield AVM OLSXY estimates to be off, on average (in absolute value), by $8,770 in 56.6% of its OLSXY estimates. In addition, Dr. Kilpatrick undermines his own assertion that appraiser standards require that an appraiser must be able to use statistical techniques (an AVM) correctly.[179] These errors in the trend surface coefficients render the Greenfield AVM estimates of value inaccurate, imprecise, and unreliable.

### E. Dr. Kilpatrick's Greenfield AVM Incorrectly Calculates Distances Using Latitude and Longitude

142. Dr. Kilpatrick incorrectly uses the latitude and longitude coordinates of CoreLogic data to calculate Euclidean distances between each Subject Property and its corresponding regression observations.[180] He also incorporates latitude and longitude coordinates in the OLSXY model "to approximate distance between the subject property and selected sales observations."[181]

[178] Legendre and Legendre, *supra* note 176.

[179] Kilpatrick Report at 26.

[180] Kilpatrick Report at 34, Appendix 5-1 at 45.

[181] Kilpatrick Report at 40.

143. The Greenfield AVM uses latitude and longitude as Cartesian (x,y) coordinates to calculate distance. This technique is incorrect and inaccurate because the distance between two degrees of latitude is not the same as the distance between two degrees of longitude in the United States due to the curvature of the earth.[182] Several projection techniques that account for the curvature of the earth are widely known and available to convert latitude and longitude into a form that allows accurate distance calculations. For example, the Universal Transverse Mercator ("UTM") projection performs the necessary conversions to calculate accurate distances, and computer software that performs UTM projections is readily available.[183]

144. Although this error is repeated in the selection of regression observations for every Subject Property, the extent to which it biases the Greenfield AVM estimates of value is not easily discernible. When the accurate distance between two points is small (*e.g.*, less than 10 kilometers, or 6.21 miles), the error is negligible. But, as the actual distance between two points increases (*e.g.*, to beyond 10 kilometers), the error from using latitude and longitude to calculate distances becomes larger. In some counties, the Greenfield AVM might be able to find sufficient regression observations within, for example, ten kilometers of a Subject Property, making the error from using latitude and longitude to measure distance negligible. But, in geographically larger counties, the error from using latitude and longitude to measure distance can be much larger. Many of the regression observations in Figure 5 are more than ten kilometers (6.21 miles) away from the Subject Property, making this error in the calculation of distance especially egregious.

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[182] *See* Ayres, F. Jr. (1954), *Theory and Problems of Plane and Spherical Trigonometry*, McGraw-Hill, New York for a discussion of using latitude and longitude to measure distance. *See also* Love, R.F. and Morris, J.G. (1972), Modelling Inter-City Road Distances by Mathematical Functions, *Operational Research Quarterly*, 23:1, pp. 67-68.

[183] For example, utility programs to perform this conversion can be found at the National Geodetic Survey web page, available at http://www.ngs noaa.gov/TOOLS/utm.shtml (last accessed on 6/9/2014).

145. To correct this error, the latitude and longitude of all of the CoreLogic sales and the Subject Properties would have to be correctly converted into Cartesian coordinates or a similar set of coordinates that can be used to calculate distance accurately. With this correction, the Greenfield AVM would select a different set of regression observations, which, in turn, would lead to different estimates of value for any affected Subject Property. This systemic error makes the Greenfield AVM estimates inaccurate, imprecise, and unreliable.

## X. Conclusion

146. In my opinion, the Greenfield AVM is so fundamentally flawed that it produces inaccurate and unreliable results. The Greenfield AVM selectively ignores the best indicators of market value: the selling prices of the Subject Properties. The Greenfield AVM uses a results-driven data filter that, among other things, makes it look more precise than it actually is (when using unfiltered data). The Greenfield AVM also inappropriately uses future tax assessed values to estimate retrospective selling prices. The Greenfield AVM assumes, with no support, that the market area for each Subject Property is the entire county in which it is located. In addition, the Greenfield AVM routinely produces illogical negative coefficients for housing characteristics that positively affect house values. The Greenfield AVM contains two computation errors: it fails to standardize latitude and longitude in the OLSXY model, and it fails to properly convert estimates of the dependent variable (on the log scale) into dollars. Dr. Kilpatrick uses the Greenfield AVM to identify 208 out of the 672 Nomura Subject Properties as overvalued using a scientifically unsupportable level of statistical significance. In his calibration exercise, Dr. Kilpatrick manipulates the CoreLogic data to bolster his claim that it meets or exceeds industry standards regarding the accuracy and reliability of AVMs. Lastly, the Greenfield AVM fails to correct for heteroscedasticity and spatial correlations present in the CoreLogic data. In short, it

is my opinion that if Dr. Kilpatrick were to correct all of the flaws that I have identified in this affidavit, then the Greenfield AVM would not support his conclusions that the original appraisals of the Subject Properties were overvalued and, therefore, the loan-to-value ratios disclosed in the Prospectus Supplements were incorrect.

Hans R. Isakson, Ph.D.

SWORN to before me
this 20th day of February 2015

Notary Public

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